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On the Chilean Pension Funds Market

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On the Chilean Pension Funds Market

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Dedication

My family is the most important thing of my life. I would not have been able to finish this dissertation without the permanent and systematic support of my lovable wife Ximena, my daughter Paula María, and my sons José Cristóbal and Andrés Felipe. They sacrificed several weekends and personal activities to motivate me to continue working on this project. I thank each of them not only for the invaluable comprehension and dedication but also for their eternal love. I also dedicate this document to my parents who taught me to be perseverant in this world.

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On the Chilean Pension Funds Market

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In 1981, the Chilean Social Security System was reformulated from a Defined-Benefit program to a Defined-Contribution one. The new law requires that only private pension fund managing companies called Pension Fund Administrators (PFAs) handle individual saving accounts and return a minimum yield on funds to their affiliates. An examination of the investment behavior of the PFAs reveals a great likeness in portfolio returns. The mechanism used by PFAs to achieve similar performance is to mimic their asset allocations and domestic stocks trading. The benchmark explains more than 95 percent of portfolio performance variability across pension funds. The asset allocation weights are equal across PFAs and there exists a high positive correlation among domestic stock weights. PFAs copy the asset selection in large market capitalization stocks. The legal framework of the reformed system encourages fund managers not to deviate from the average system return by herding in their investment decisions.

Regarding the relationship between fund flows and performance and the determinants of investors' (pensioners') choice of PFA, evidence is found that (1) a positive and non-linear relationship exists between fund flows and performance, (2) past-

12-months performance and rankings are relevant to consumers, although larger accounts are more sensitive to these variables, (3) the number of customers in a PFA is stable even if it performs poorly, and (4) the marketing strategy commonly carried out by the best performer is advertising, while PFAs in the bottom positions tend to expend less on advertising. These findings suggest that the best performing PFA according to rankings is slightly rewarded with larger flows from elderly or wealthier accounts. However, the instability in the ranking position indicates that customers do not flock toward the top performer. The market share across PFAs has tended to stay constant over time, indicating the short-lived effects of advertising.

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Chapter 1: Introduction and Literature Review

1.1. INTRODUCTION

In the Chilean capital market, pension funds are the largest institutional investors with an asset value of US$35 billion, equivalent to 50 percent of the country's GDP. In contrast, life insurance companies and mutual funds represent 13 percent and 5 percent of Chile's GDP, respectively. Chilean pension funds started their activities as of May 1981 after the government reformed the social security system from a defined-benefit program to a defined-contribution one. Edwards (1998) characterizes the Chilean reform as pioneering in Latin America and stresses that it has contributed to the enlargement the Chilean saving rate from less than 10 percent to 29 percent. In fact, this reform has been implemented in nine other Latin American countries: Peru (1992), Argentina and Colombia (1993), Uruguay (1995), Mexico, Bolivia, and El Salvador (1996) and Nicaragua and the Dominican Republic (2001).[1] Diamond (1993), Edwards (1998), and Iglesias and Acuña (2001) give a deeper and detailed description of the excellent performance of Chilean economic reforms during the 1980s.

In spite of its economic benefits, the Pension Funds Act has been criticized for implicitly encouraging a lack of diversification due to constraints on the portfolio investment administered by the pension fund managing companies, called Administradoras de Fondos de Pensiones or Pension Fund Administrators (PFAs). According to the Pension Funds Act, the government supervises both PFA operations and investments. More importantly, it is obligated by law to assure both a minimum guaranteed return (MGR) on the clients' funds and a minimum pension stream to

[1] Diamond (1993), Edwards (1998), and Iglesias and Acuña (2001) give a deeper and detailed description of the excellent performance of Chilean economic reforms during the 1980s.

pensioners.[2] The commitment to attain this minimum yield is transferred directly from the government to the PFAs. The MGR corresponds to the lower value between: either the weighted average real return minus 2 percent, or the weighted average real return minus 50 percent of its absolute value. The law requires each PFA to hold a Margin Account equivalent to 1 percent of the fund value to warrant this commitment, which is directly funded by PFA's shareholders. If a PFA does not achieve the MGR, it must cover the difference between the current yield and the MGR with funds from the Margin Account. In addition, its equityholders must restitute the initial value of this account within 15 days. If a PFA fails in doing so, it is immediately liquidated. In contrast, if a PFA gets a return superior to the yield between the weighted average real return plus 2 percent and the weighted average real return plus 50 percent of the absolute value of the average return, whichever is higher, this excess would be accumulated in the Yield Fluctuation account. This account is utilized to cover the event that the PFA does not realize the minimum return in the future.

The purpose of this dissertation is to analyze the investment behavior of pension funds with regard to this legislation and how their clients make decisions with respect to which PFA to select.

In Chapter 1, I review the literature on theoretical models of moral hazard and relative performance evaluation that are related to the type of compensation contract offered by the Chilean government to PFA managers. Also, I review the herding literature, presenting theoretical models and empirical findings to explain similarities in returns perceived by PFAs. Finally, I examine the literature on the relationship between past performance and fund flows to explain how clients make their decisions.

[2] The Pension Fund Act refers to clients as "afiliados" (i.e., *affiliates*).

In Chapter 2, I provide the background of the Chilean pension fund system, describing its evolution and the main points of the regulatory law related to investment constraints and the minimum guaranteed return.

In Chapter 3, I study how the new system under the Pension Funds Act has influenced the investment style of money managers. Specifically, the questions I address are: (i) how much of the return of each PFA is explained by the asset allocation, (ii) how pension funds are allocated among asset classes, and (iii) what mechanism the funds implement to reach similar returns. I do not argue whether the new system is optimal in terms of resource allocation or whether a PFA's behavior is correct. Rather, I claim that the current legislation—which is based on the principle of relative performance evaluation—forces fund managers to stay as close as possible to the weighted average primarily due to the threat of punishment. I find that in general PFAs tend to hold the same asset allocation. The benchmark, defined as weighted average return of industry, explains more than 99 percent of return volatility. When testing the differences in asset allocation, the null hypothesis that the weight coefficients are equal among funds is not rejected. When pension funds change their asset allocation, fixed-income securities become perfect substitutes within themselves in yield, exhibiting great diversity of correlations. However, the correlation of the stock weights across funds is perfectly positive. Granger-causality tests suggest that the three largest funds are the leaders, and they move the market. Medium funds have influence on the weighted average return; however, they tend to follow the three leaders, who account for more than 60 percent of assets value. Finally, I examine stock trading using the methodology of Lakonishok, Shleifer, and Vishny (1992) and Sias (2004) to appraise the possibility of herding. The herding level tends to increase quickly (i) with the number of funds trading, (ii) within the quintile Q1 of the largest market capitalization stocks, and (iii) during the Asian crisis.

In Chapter 4, I examine how the clients choose among funds and how the pension funds compete to attract customers. In particular, I consider whether past performance or ranking on performance influences investors' decisions. I also examine if advertising is commonly used to divulge information about significant events such as past performance and reductions in fees. I find evidence of a positive and non-linear relationship between flows and past-12-months performance. I also find that the number of clients in each fund remains relatively steady despite some funds being classified as losers in the ranking—that is, clients are less performance-sensitive to poor performers. I also document a negative relationship between net flows and both fixed and variable fees. The biggest marketing efforts are mainly carried out by the winner fund in order to promote its past performance. Funds that rank lower tend to spend less on their marketing strategy. Finally, I find that the best performer increases its share of advertising expenses in a period between 1-month and 3-months.

1.2. LITERATURE REVIEW

1.2.1. Moral Hazard and Relative Performance Evaluation

Conceptually speaking, the Pension Fund Act may be visualized as the contract offered to PFAs (Agents) by the government (Principal). Managers must attain at least the minimum guaranteed return (MGR), which is calculated from the average return of all pension funds (benchmark). Managers who do not obtain this MGR are punished. The Chilean government evaluates pension fund managers based on the weighted average return across funds, that is, under relative performance evaluation.

The form in which fund managers are rewarded influences their behavior, and simultaneously, their actions (unobserved) affect the government's wealth. In general, the principal's main problem is how to design a contract or compensation to induce the appropriate efforts of agents when the principal is unable to control non-observable efforts (moral hazard). When writing a contract, the principal must include (i) individual rationality and (ii) incentive compatibility. The first concept represents the manager's willingness to participate in this market, taking into account the opportunity cost. The second one means if the principal wants a manager to implement a specific action, that action should be congruent with the manager's benefit maximization.

The PFA performance (r) depends on the manager's efforts (e) and a random component (P), which is beyond his control. If a PFA manager is risk-averse, then the government should compensate him for bearing risk due to changes in his salary triggered by the exogenous term. In this case, there exists a trade-off for the manager between making a reasonable effort and reducing the amount of risk. Sharpe (1981) postulates that specialization and diversification are two reasons to prefer a manager team to a single agent. However, Barry and Starks (1984), continuing with Sharpe's notion, argue that risk-sharing is a sufficient argument to select multiple agents. This principle means that sharing independent risks reduces the total cost of risk-bearing.

Holsmtrom (1979), in one of the leading papers in the moral hazard literature, shows that the wage contract is increasing in relation to single agent's output and that any information on actions may be used to design the contract. Holmstrom (1982) widens his analysis to agent teams and claims the actions of one agent are informative for the principal of other agents, especially if their outputs are correlated. In this case, competition among workers is fruitful for the principal. Lazear and Rosen (1981) show that when agents do not collude, wages based on rank-order contest provides incentive to agents to acquire skills and increase their efforts. Mookherjee (1984) extends the moral hazard problem to the multiple agent case to explore the use of relative performance evaluation (RPE) in optimal incentive contracting. However, the principal cannot identify with precision whether a high performance is the result of high effort (eh) realized by the manager or high shock (Ph).

One way to solve the problem for defining a reward scheme is to consider observable factors that allow identifying the type of effort implemented by each PFA manager through relative performance. Holmstrom (1982), Gibbons and Murphy (1990), and Prendergast (1999) say that the optimal compensation should be based on relative performance since it is more informative about the fund managers' efforts (Informativeness Principle). The manager's reward would depend on his performance and peer-performance. In effect, Gibbons and Murphy (1990), in their empirical study of CEO compensation, state that RPE insulates agents from random shocks, which influence performance. Despite RPE reducing risk exposure of a risk-averse agent, a manager may realize efforts that affect the average return of the group (collusion) when compensation is based exclusively on RPE. They provide evidence that CEOs are evaluated relative to market movements rather than industry movements. Mookherjee (1984) argues that the principal may extract maximum advantage from relative performance clauses. This implies that under perfect correlation in agents' performance, the principal may get the first best by setting heavy penalties on agents. Naik and Maug (1995) derive an optimal contract for delegated portfolio management that contains RPE; they show that managers ignore their own superior information and "go with the flow." If a contract is contingent on performance relative to a fund manager's peers, then asset allocation realized by that manager depends not only on expected returns but also correlation of the returns with those they are compared with.

The literature on multiple agents indicates that there are often multiple Nash equilibria ranked differently by agents and investors—that is, agents could cooperate to reach an outcome other than that desired by the principal. In their model, Naik and Maug (1995) conclude that an RPE contract induces smart managers to herd with dumb ones in spite of their superior information. This is the opposite of what Scharfstein and Stein (1990) observed. Herding arises due to the RPE nature of the compensation contract. Ramakrishnan and Thakor (1991) explore benefits to the principal of inducing cooperation among agents (sharing tasks), as managers may work either individually or in cooperation. They show that if two tasks are uncorrelated, the principal prefers a cooperative game to a competitive one, but if tasks are correlated and the compensation scheme of each agent depends on what the other does, then managers tend to collude. If tasks are correlated and the principal organizes them in a competitive system, the expected contracting costs decrease monotonically as the correlation coefficient increases.

Unlike Ramakrishnan and Thakor (1991), Pichler (2002) considers not only that the principal is risk-averse but that managers may either herd or ignore others' efforts. He examines portfolio management in teams under moral hazard, analyzing noncooperative and cooperative forms. In the first form, managers are not able to monitor each other. In contrast, in the second form, they can engage in side contracts. His conclusion is that the optimal contract depends on the risk attitudes of both principal and managers. If managers are risk tolerant, the efficient contract is not to herd, which is a strictly competitive contract (noncooperation form). If a manager is risk-averse, a competitive contract imposes risk on individual managers because some managers are winners and some are losers. The intention of managers to herd will depend on (i) relative strength of incentives and (ii) the risk attitude of the manager. In cooperative form, if a manager is risk-averse, the first best (optimal solution) requires that the wage be based on team performance and not on an individual manager's performance. If a manager is risk-tolerant, then first best without herding can never be achieved if cooperation is infeasible. If cooperation is feasible among managers, the cost of discouraging herding decreases for some parameters. Kapur and Timmermann (2002) examine how portfolio choice changes with the compensation schemes by examining contracts that reward a manager when he out-performs his peers' performance and penalizes him when he under-performs. They conclude that those contracts tend to exacerbate herding in managers by holding the benchmark portfolios and lowering risk premium in stocks.

In sum, RPE-based contracts induce managers to collude with each other, creating the tendency to herd investment decisions.

1.2.2. Herding as Investment Behavior

In the financial literature, herding is defined as a decisive intention of managers to copy investment decisions made by others regardless of their own information (intentional herding)[3]. Bikhchandani and Sharma (2001) distinguish 3 possible reasons to herd: (i) manager thinks others know something that he doesn't and their actions are informative for him, (ii) compensation contract implicitly rewards imitation, and (iii) preferences for conformity driven by specific payoffs that affect compensation of others. The term herding is referred to as informational cascade by Bikhchandani, Hirshleifer and Welch (1992). Banerjee (1992) argues that herd externality is inefficient from social viewpoint. Scharfstein and Stein (1990) describe a herding model of reputation, where there are two types of agents, smart and dumb, and the investor infers their abilities even

[3]See, for example, Bikhchandani and Sharma (2001), Bikhchandani, Hirshleifer, and Welch (1998), Hirshleifer and Teoh (2001), and Devenon and Welch (1996).

if their investment decisions are identical. Herding arises when the smart manager makes her choice and then the next manager follows this choice, regardless of his own signals, because low performance occurs by chance and high performance is due to managers' capabilities.

Several empirical papers have documented different herding levels. Lakonishok, Sleifer, and Vishny (referred to as LSV) (1992) wrote the determining document in the literature on herding measure. LSV (1992) define herding as the tendency of funds to trade a given stock together and in the same direction. A group of funds exhibits herding when there is unbalance between funds that buy and funds that sell a given stock. There is herding behavior when a proportion of funds that trade in a stock in the same direction (buy–sell) is above the expected proportion of funds trading in that direction under the null hypothesis of independent trading decisions by the funds. This kind of herding appraisal allows the differentiation of spurious herding from intentional herding as defined by Bikhchandani and Sharma (2001).

LSV (1992) look at 769 pension funds, managed by 341 different portfolio managers between 1985 and 1989, and find the herding level was not significant (2.7 percent). Grinblatt, Titman, and Wermers (1995), who use the LSV (1992) measure, examine the extent to which herding and momentum investing affect the performance of 155 mutual funds over the period 1975-1984 and find weak evidence of herding strategies (2.5 percent). Wermers (1999) analyzes the trading of the mutual fund industry from 1975 through 1994 to determine whether funds herd when they trade stocks and to investigate the impact of herding on stock prices. Using the LSV (1992) approach, he finds a low level of herding among mutual funds (3.4 percent); however, there is a stronger herding effect among growth-oriented mutual funds and in small and winner stocks. Nofsinger and Sias (1999) study two types of shareholders (institutional and individual) and focus on annual changes in ownership, exploring how changes in institutional ownership are related to lag returns (feedback trading) and momentum. Their results reveal positive annual changes in institutional ownership and returns. The decile of stocks experiencing the largest increase in institutional ownership outperforms by more than 31 percent the decile experiencing the largest decrease. Choe, Kho, and Stulz (1999) find that foreign investors herded in the Korean market before the Asian crisis in the smallest quintile of market capitalization stocks (6.9 percent) but not during the crisis. Lobao and Serra (2002) test herding in Portuguese mutual funds over the period of 1998-2000 and evidence a strong herding level (11 percent).

A different approach to measure herding is that described by Sias (2004). He examines trading activity of five institutional investors for 60 quarters and addresses the question of whether institutional investors herd. He analyzes a cross-sectional correlation between demand for a security last quarter and demand for the security this quarter. Unlike the LSV (1992) approach, Sias's method captures the effect that traders may follow their own pattern or another's over adjacent periods. The herding value he finds is equally explained by a manager's own trading activity and by others' trades.

1.2.3. Past Performance and Fund Flows

Many articles in the financial literature examine the relationship between past performance and money flows. Ippolito (1992) presents evidence that funds that do better than the market tend to experience a more positive response than those that do worse. Sirri and Tufano (1993) show that top-performing funds receive net inflows, yet funds that perform poorly do not lose many assets. Gruber (1996) illustrates that the flow of new money into the best performing funds is much larger than flows out of the poorer performing funds. Sirri and Tufano (1998) study household behavior by analyzing fund flows in U.S. mutual funds and find that consumers are fee-sensitive and react asymmetrically to past performance, especially in those funds that realize more marketing activities as a mechanism to reduce costly search.

Del Guercio and Tkac (2002) examine in mutual funds and pension funds the relationship of flow-performance under three flow definitions and show that pension fund clients react more slowly to poor performers than do mutual fund investors. Mutual fund investors strongly flock toward top performing funds. Huang, Wei, and Yan (2003) postulate that investors recognize increase in volatility and hence fund flows are less sensitive when performance is more volatile. Zheng (1999), using flow measure in dollars, finds top performer funds get more money, but this is a short-run effect. Likewise, Hendricks, Patel, and Zeckhauser (1993) find short-run persistence level of superior performance (hot hands).

Goezmann and Ibbotson (1994) claim the best performing managers in the past are likely to be the best performing managers in the future. Goetzmann and Peles (1994) suggest that people tend to buy funds that have done well in the past, but after purchasing a fund, if that fund performs poorly, these investors are reluctant to admit their mistake due to cognitive dissonance. Brown, Harlow, and Starks (1996) study how incentives affect fund managers' behavior by viewing the mutual fund industry as a tournament. Top performers relative to their peers tend to receive higher compensation since investors flow toward funds with higher performance. This produces an adverse incentive on fund managers to change their portfolio risk when their performance is behind that of their peers as a way to maximize their compensation. Similarly, Chevalier and Ellison (1997) argue that a positive relationship between fund flow and performance encourages fund managers to alter the riskiness of the portfolio. Relative performance evaluation generates the undesirable incentive in managers to increase portfolio volatility because investors are top fund seekers.

In the following chapters, I use this bibliography to analyze the Chilean pension funds. (All the tables referred to in the following chapters appear near the end of the document as appendices.)

Chapter 2: Overview of Chilean Pension Funds

2.1. INTRODUCTION

In this chapter, I provide general information on Chilean pension funds from 1981 to 2001, specifically:

- the causes that drove the reform of the Chilean Social Security system from a defined-benefits program to a defined-contribution one
- the evolution of asset values
- the main features of the pension fund law relative to investments and minimum guaranteed return
- general statistics of market share, average returns, revenues, expenses and assets.

2.2. BACKGROUND

2.2.1. Overview of the Chilean Social Security System Reform

The Social Security system began functioning in 1924 under the form of pay-as-you-go (PAYG), a defined-benefit program. PAYG was a collective contribution program with several pension schemes for different types of workers. In fact, each program, administered by institutions with distinct objectives, granted a variety of pensions depending upon industry category, worker's age, and the number of working years. In the 1960s, as a consequence of a demographic trend, the PAYG system started progressively exhibiting severe problems of financing. In the period 1960-1970, the number of contributors per retiree decreased from 10.8 to 4.4. Additionally, the disparity in the benefits conferred to workers of the same working situation (due to political privileges), the mismanagement of pension funds invested (non-indexed to inflation rate and loans to workers), and the increasing government funding obligated the government to reform the pension system.[4]

The Pension Funds Act replaced the PAYG system in May of 1981. The fundamental tenet of this reform lies in the creation of mandatory individual savings accounts administered exclusively by private fund managing companies called Administradoras de Fondos de Pensiones or Pension Fund Administrators (PFAs). The government office called the Superintendencia de Administradoras de Fondos de Pensiones or Superintendence of Pension Fund Administrators (SPFA) strictly regulates PFAs' operations and investments carried out on behalf of Pension Funds.[5] In addition, by regulation, the government is responsible to guarantee a minimum cash flow stream to pensioners and a minimum guaranteed return (MGR) on funds managed by PFAs. The accountability for achieving this MGR is delegated to PFAs.

Regarding compulsory savings, dependent workers must contribute 10 percent of their taxable salary to their individual saving accounts monthly. A supplementary percentage (around 3 percent) is charged to finance management fees and disability–life insurance. Savings accounts cannot be used as collateral by workers to warrant any financial transaction. The employers are the responsible agents to deposit these monthly contributions directly to each PFA. Each worker has the freedom to choose any PFA; however, she cannot divide her individual savings among different pension funds. The law prohibits PFAs from charging any fees on cumulated funds in the savings accounts

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[4] SPFA (1999), Edwards (1998) and Godoy and Valdes-Prieto (1997) provide good overviews on the historical evolution of the Chilean pension system.

[5] The Pension Fund is the sum of individual saving accounts. A PFA is a privately-owned or publicly-owned entity with a board and shareholders. Both institutions possess independent financial statements and portfolio holdings. The current legislation also regulates the "conflict of interests" between the PFA and the Pension Funds with respect to the participation of PFAs on behalf of Pension Funds in shareholder meetings of security issuers.

(asset value) but exclusively on monthly taxable salaries. Even though PFAs are allowed to charge fees on transfer of the client's funds, no institution does.

Every month, workers must pay both variable and fixed fees for PFA services. The variable fee is a percentage of a worker's taxable income. This percentage ranges from 2.3 to 2.8 percent of a worker's income; the average charged by PFAs in 2001 was 2.5 percent. The fixed fee is just a flat rate that is not based on income; the average fixed fee is $581 (US $0.90).[6] The variable fee for managing the funds accounts for 85 percent of PFAs' total revenue (the other 15 percent is capital gains from investing in the market). The worker's taxable income is defined as the monthly salary before withheld taxes and health care deductions. Those with higher salaries definitely pay higher fees because their monthly deposits are larger; however, the law sets a maximum of $1.0 million (US $1,500) of a worker's salary from which to make mandatory contributions to a savings account and from which to calculate the variable fee. For instance, if a worker's salary is $2.0 million, her monthly contribution to her savings account would be $0.1 million, and the PFA would get a monthly variable fee payment of $25,581. However, if a worker is laid off or otherwise loses her job, no monthly contribution is deposited in her account, and no monthly fee can be charged by the PFA, even though the PFA must continue to manage her savings account. If she starts working again, she has no legal responsibility to pay any "back" fees for having her fund managed during the months she was unemployed.

Regarding the number of funds under management, each PFA was initially allowed to manage just one fund. Legislative changes in 2000 gave PFAs the authority to administer two funds (Type I and II). The main differences between them are their

[6] Data is expressed in Chilean pesos. I present some tables in U.S. dollars just to provide to readers a general overview of the system, but findings are computed using local currency. The amount of $581 converted to US dollars is US$ 0.90.

investment limit and the type of client they serve. For instance, for government bonds, the maximum limit of investment for the funds Type I and II is 80 percent and 50 percent, respectively. Fund Type I is designed to draw clients who are near their retirement date; however, a contributor cannot divide his PFA-managed savings between both types of funds. In August 2002, lawmakers authorized the running of five funds as a way to spread out the investment alternatives for clients (Funds A, B, C, D, and E).[7] Currently, each worker may select to split his savings between two funds but in only one institution.

2.2.2. Evolution of Pension Funds System

The new system began to operate with twelve PFAs and US$296 million in asset value. As of 2001, only 7 PFAs remain in the market with the total value in funds of US$35 billion, equivalent to nearly 50 percent of the Chilean GDP. Although the system reached a maximum of 21 managing companies in 1994, this number diminished to seven by 2001 as a result of eleven acquisitions and three license cancellations. Iglesias and Acuña (2001) blame the excessive and growing concentration in this industry by economies of scale on the number of clients and the legal barriers required of a mandatory margin account (equivalent to 1 percent of pension funds assets). However, the pension system was, from the beginning, dominated strongly by three large pension funds. The three largest institutions, Provida, Habitat, and Cuprum, have concentrated a great proportion of market share. In fact, from the first year of operation of the pension fund system, this group has concentrated approximately 71 percent of the funds' value.[8] Table 2.1 depicts the evolution of number of institutions, pension funds value (as percentage of GDP and in U.S. dollars), yearly real return, and market concentration

[7] Fund A is a long-term investment plan that invests in securities with a greater weight in stocks. In contrast, Fund E is highly concentrated in fixed income securities and designed for those who are near their retirement date.

[8] This point attains an important relevance when we talk about the Minimum Guaranteed Return determined on the base of the weighted average return of the asset values.

given by Herfindahl index. The Herfindahl index (HI) is a measure of market concentration and is calculated by squaring the market share of each PFA and then summing those squares. As of 2001, when there were seven PFAs, the HI value was 0.21, which is similar to the HI value in 1981, when there were twelve funds. Some PFAs were neither able to achieve the break-even point nor capture significant market share, so their inevitable destiny was the merger. Merged PFAs reported consecutively negative net operating incomes because of the low client level, despite generating similar returns to other institutions.

In the sample period 1997:06–2001:12, the number of PFAs went from thirteen (in 1997) to seven (in 2001) as a result of a series of mergers. Mergers have been the most effective mechanism used by funds to increase market share. The absorbed institutions were not capable of achieving the break-even point in the number of clients. Table 2.1 illustrates the evolution of the market share of survivor and defunct funds through time measured by the number of clients (Panel A) and by asset values (Panel B). By 2001, the largest fund (PFA Provida) has 40 percent of all clients and 31 percent of assets. With 6.9 percent of the clients but 17.5 percent of the assets, PFA Cuprum has the greatest account value per client. Another crucial feature in the sample period was the drop in mean value of monthly variable fees across funds from 3.0 percent to 2.5 percent. To exemplify the likeness in performance, Table 2.2 presents the returns distribution of pension funds for selective months.[9]. The worst performance exhibited by PFAs is during the Russian crisis (Sept-98) with an average return of -3.8 percent and a standard deviation of 0.36 percent. The average difference between the maximum and minimum monthly returns is 0.47 percent with a standard deviation of 0.24 percent. However, the average monthly difference between the largest fund return (PFA 9) and the industry

[9] The averages and standard deviations are computed with all returns.

average is 0.01 percent—the same number that results when computing this difference with a medium fund (PFA 11). The average monthly difference (not listed) between the highest performer (1.02 percent) and the next highest one (0.89 percent) is 0.13 percent, but the standard deviations of their monthly returns are identical, 1.84 percent. In addition, Graphs 1 and 2 plot the returns and differences in returns between the highest performance and next highest one and between the highest return and lowest one. It is striking that performance lines overlap each other.

In contrast, Chilean mutual funds, classified into categories such as fixed income and variable funds, epitomize a steady growth in the number of funds and dissimilarity in performance. As of December 1999, there existed 14 mutual funds with 115 funds, and in 2001, this industry was composed of 17 mutual funds and 177 funds. Their asset values, equivalent to 10 percent of PFAs' asset values, grew between those years from $2,151 million to $3,313 million. Also, regulation of mutual funds is less restrictive than that of pension funds. Investment constraints are fundamentally focused on avoiding concentration by security issuers.[10.] Neither the government nor mutual funds are obligated to guarantee any minimum return on funds. Each mutual fund may charge any fee by management on the basis of asset values. PFAs, on the other hand, cannot charge fees on asset values. Within each category, mutual funds have exhibited a wide range of management fees and returns. In fact, Maturana and Walker (1999) find that stock funds present similar returns to passive strategies, but the differences in annual returns among funds are as large as 10 percent.

[10] Unlike mutual fund regulation, PFA legislation considers liquidity and concentration factors to estimate the investment constraints. Olivares (2003) describes that the PFA constraints.

2.3. REGULATION ON INVESTMENTS AND RETURN

2.3.1. On Investments

The most striking features of the Pension Funds Act are those related to regulation on investment and the PFAs' accountability in yielding a minimum return. PFAs may invest in securities specifically authorized by law. The extensive list of choices comprises domestic securities and foreign assets such as government bonds, banking deposits, corporate bonds, stocks, mortgage-backed securities, and REIT shares. The Risk Rating Commission is the organization in charge of assessing the eligible securities for pension fund holdings. No PFA can allocate funds in assets rated in a category inferior to BBB.[11] The regulation also restrains the maximum limits of investment, expressed as percentage of funds according to (i) security, (ii) issuer, (iii) family of securities, (iv) issuers related to the PFA by ownership or management, and (v) exposure to specific risk. In light of this, the SPFA controls investments by means of *factors*. These factors are applied to an issuer's net asset value as funds value.[12] For instance, the limit of investment *by security* is equivalent to 37 percent of the pension fund value. The limit *by issuer* is a defined percentage relative to fund value, new stock issuance, and issued total stocks. Table 2.3 summarizes the main limits on investment of pension funds in the period relevant to our research and illustrates some examples of the application of these limits.

As of 1981, pension funds held basically four assets in their portfolios: government bonds, deposits in banks, mortgage-backed securities, and corporate bonds.

[11] Government bonds are rated AAA. One of many ways of supervising the investment is to use "factors" that run from 1.0 to 0.0. Securities rated below BBB receive a multiplicative factor of 0.0. Those AAA assets get 1.0. In the following paragraphs, we explain this in detail.
[12] These factors are (i) liquidity, (ii) liquid assets, (iii) concentration of major shareholders, (iv) risk rating, (v) diversification and (vi) single multiple.

Under the new Pension Funds Act, step-by-step, the government started increasing the eligibility of new assets. Stocks became part of portfolio holdings in 1985 as a product of not only the privatization process of government-owned companies but also the profound reform of capital markets. Real estate shares were incorporated in 1989 and foreign securities in 1992. Table 2.4 shows the yearly composition of portfolio holdings of the pension funds system from the beginning in 1981 to 2001. This evolution of asset holdings was highly forced by the SPFA by forbidding fund managers from investing in risky assets.

2.3.2. On the Minimum Guaranteed Return (MGR)

Article No. 37 of the Pension Funds Act establishes that in each month, each PFA will be responsible for the past-36-months annualized real rate of return of each of its funds not being inferior to whichever is lower,[13] either:

- the past-36-months annualized average return across funds of the same type minus 2 percent, or
- the past-36-months annualized average return across funds of the same type minus 50 percent of absolute value of this average return.

For example, if the weighted real average return were 4 percent, both alternatives converge at 2 percent. If the average real return of the system were either higher than 4 percent or lower than minus 4 percent, then the lower boundary would be the average minus 50 percent of this return. However, if the average real return lies between 4 percent and minus 4 percent, then the warranted return would be realized by the average

[13] Some authors have wrongly translated this article saying, "not be inferior to whichever becomes the higher."

minus 2 percent. In October 1999, the legislation extended the measure horizon from the past-12-months return to the past-36-months return.[14]

In order to guarantee this condition, the legal framework requires that PFAs keep two margin accounts. Each PFA must hold, at any moment, the equivalent of 1 percent of the value of each fund that it manages in an account called Mandatory Reserve, which is financed directly by its shareholders.[15] This reserve must be deposited in the Central Bank of Chile and invested in a portfolio similar to that of the fund. The second account, called Yield Fluctuation Reserve, is constituted by the excess of return over the minimum return. If the past-36-months current real return is the higher between the average return plus 2 percent and the average real return plus 50 percent of its absolute value, the excess is accumulated in this account. If a PFA does not achieve the MGR, it must first use the Yield Fluctuation Reserve to meet this requisite.[16] If that is not possible, the PFA must withdraw the needed money to make up this difference from the Mandatory Reserve account, and its equityholders must restore the initial value of this account within 15 days. If the PFA does not accomplish this requirement or its shareholders do not supplement the required funds, the SPFA will liquidate it ipso facto, finance the required resources to meet the yield obligation, and transfer the fund's assets to another PFA.[17]

The MGR requisite is calculated across funds of the same type, i.e., the MGR of fund Type I is absolutely obtained from the past-36-months weighted average real return

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[14] Valck and Walker (1995) had already criticized the short evaluation period and postulated that extending the evaluation horizon would allow different investment strategies. Later, I analyze how this change affected the behavior of pension funds.

[15] As the system has not reached yet its maturity (inflows>outflows), each PFA must permanently finance the requirement of the Mandatory Reserve.

[16] Each fund managed by a PFA possesses its own Mandatory Reserve and Yield Fluctuation Reserve. Both Margin Accounts are independent among funds of a PFA and cannot be combined among funds to meet the deficit of return of a fund in particular.

[17] Professional organizations, unions, and local companies owned most small and merged pension funds. Currently, international financial corporations manage five of the seven pension funds. Due to Mandatory Reserve requisite, large companies with good access to the capital market possess a competitive advantage over unions and professional organizations to raise new money.

of all funds defined as Type I. This means that the performance of a type of fund is unrelated to what other funds of other types realize. In fact, the Pension Funds Act tries to unlink the funds' performance administered by each PFA by setting Margin Accounts and MGRs per type of fund. Edwards (1998) affirms that this specific constraint causes PFAs to handle similar portfolios. Likewise, Valck and Walker (1995) and Iglesias and Acuña (2001) state that this return obligation and the short evaluation period tend to punish divergent portfolios.

Chapter 3: Investment Behavior of Pension Funds

3.1. INTRODUCTION

This chapter examines the investment behavior of the Chilean Pension Funds. I start by documenting the main statistical patterns of the returns. Then, I examine the main determinants of such returns.. Specifically, the issues I examine are: (i) how pension funds are allocated among asset classes, (ii) how much of the return of each PFA is explained by the asset allocation, (iii) how similar are the funds' returns, and (iv) what explains the similarities across fund returns. In addition, I use the methodologies of Lakonishok, Shleifer, and Vishny (1992) and Sias (2004) to measure herding activity.

To briefly preview the results, I find that the mechanism used by pension funds to achieve similar performance is to mimic their asset allocations and domestic stocks trading. I also find that the asset allocation weights are equal across pension funds and there exists a high positive correlation among domestic stock weights. In relation to stock holdings, I find that pension funds particularly copy the asset selection in large market capitalization stocks. I conclude that the legal framework encourages fund managers not to deviate from the average system return by herding in their investment decisions. The contract offered by the government to managers is based on RPE, which, as discussed in the previous chapter, may be inducing PFA managers to collude in their actions to avoid being penalized.

3.2. METHODOLOGY AND HYPOTHESES

3.2.1. Data and Methodology

I utilize a monthly data set collected on the fund Type I directly from the Superintendence of Chilean Pension Funds for the period June of 1997 and December of

2001 in Chilean pesos. It contains detailed information on monthly portfolio holdings, quota value, and financial statements of each pension fund. This data comprises all PFAs. Our sample includes the thirteen institutions that functioned in 1997 and the seven that still survived in 2001. This allows us not only to keep our study free of survivorship bias as argued by Mankiel (1995) and Brown and Goetzmman (1995) but also to analyze the investment behavior that the merged PFAs followed and compare it with that of the survivor PFAs. Monthly information on stock prices, stock index value, and issued total stocks come from a Chilean Stock Exchange database. I exclusively consider the Type I fund because it has more observations compared to the Type II fund, which started its operation in 2000 after an amendment to the legislation. The two fund types are completely unrelated since each one has its own investment limits and the minimum return condition is computed across the same type of fund.

Although I display descriptive information on the pension funds system in some tables using both Chilean pesos and U.S. dollars; the data and findings are computed in Chilean pesos. In fact, PFA share values, asset allocations, stock prices, and portfolio holdings are processed in Chilean pesos. There is no benchmark portfolio in the Chilean market, aside from two stock indices prepared by the Santiago Stock Exchange.[18] To compare the investment strategy of pension funds, I define the benchmark portfolio as the summation of total holdings of the pension funds industry. The benchmark performance is calculated as defined in the law: the average return across funds weighted by asset values of each fund. The asset allocation of the benchmark corresponds to total money allocation realized by all PFAs in different assets. However, although the weighted average portfolio is biased by the largest three funds, I compute an equally weighted portfolio from all funds (simple average) in both return and asset allocation weights on

[18] The indices are IPSA formed with the 40 largest stocks and IGPA with all stocks.

five asset classes. In the case of pension funds, the set of alternatives is provided by investment constraints and by weighted average portfolio. As a reference, in the regulatory benchmark portfolio, the smallest and largest fund weights, measured by asset values, account for 2 percent and 33 percent, respectively, of the total, but in the simple average portfolio, both represent 8 percent.

This study covers the period beginning in June of 1997 to take advantage of the fact that most of the data starting from this period is available electronically. However, I also provide readers with an overview of the Chilean pension system using yearly information from May of 1981 to December of 2001 obtained from the Bulletins published by the Superintendence as well as a special SPFA study called "Evolución del Sistema Chileno de Pensiones (Evolution of the Chilean Pension System), 1981-1997." These bulletins compile statistics on the clients, pension funds, fees and fund asset values. Table 3.1 presents this descriptive statistics in Panels A and B.

The period under study (June 1997 to December 2001) includes several events that provide very useful variation that will allow a rich understanding of the behavior of pension funds. Specifically, the period includes: (i) the financial crises of Asia, which lasted from 1997:06 to 1998:01, and of Russia in 1998:08, (ii) a series of mergers/acquisitions that reduced the number of PFAs from thirteen to seven, (iii) a deep fall in domestic share portfolio weight from 31 percent to near 10 percent of total pension fund assets, and (iv) a change in legislation that widened the evaluation period to calculate the MGR from 12 months to 36 months.

In relation to the portfolio holdings, the asset allocation is divided into five categories: shares, bonds, banking deposits, foreign securities, and mortgage-backed securities together with REIT shares.[19] To describe the performance of the funds, I calculate both simple arithmetic and weighted averages of the industry return. I define the variable premium in returns as the difference between the return of fund (i) and the benchmark return (both simple and weighted average), and I define the variable premium per asset class as the difference between a fund's asset allocation weight and the asset allocation weight of the whole industry (both simple and weighted). Stocks are clustered by quintiles of market capitalization (size), by economic sector, and by ranking of size within each quintile. For each month, I compute the quintiles, returns, and ranking based on the monthly stock returns and values.

3.2.2. Hypotheses

I postulate that the RPE-based contract defined as MGR encourages pension fund managers to achieve similar returns in order to not deviate from the weighted average return. (Given the regulation, this industry return emerges as natural benchmark.) This hypothesis suggests that the expected behavior of a fund manager would be to replicate the investment decisions made by others in response to financial sanctions that would harm his shareholders if his performance lies below this minimum return. I investigate the strategic asset allocation and stock trading activity carried out by fund managers. The study of stock trading activity and its asset selection is of real importance to test the existence of likeness in returns, considering that stock holdings weight not only dramatically decreases by two-thirds through time, but is also the main variable-income asset.[20] In fact, the other four assets belonging to the asset allocation correspond to fixed-

[19] Originally, I considered seven asset classes: stocks, government bonds, corporate bonds, foreign assets, deposits, MBS, and REIT shares; and our findings were not significantly different from those with five asset classes.
[20] Replicating investment strategy does not necessarily imply similarity in returns. Lakonishok et al. (1992), Grinblatt et al. (1995), Choe et al.(1999) and Wermers (1999) find that, despite fund managers tend to copy investment strategies, their performances are different.

income securities since a great proportion of foreign assets is allocated in bonds. The questions addressed are:

1. how much of the return of each PFA is explained by the "benchmark"—i.e., whether pension funds are pursuing an asset allocation such that they achieve performance analogous to the industry average,
2. how pension funds allocate among asset classes—in other words, how diverse PFA's investment policy is relative to benchmark portfolio,
3. what mechanism the funds implement to reach similar returns. I test the time-series of the asset allocation weight deviations with respect to benchmark portfolio are different among funds and whether managers tend to mimic the stock trading activity.

3.3. MODEL SPECIFICATION

3.3.1. On Asset Allocation

To address the first question—the importance of the weighted average return (the benchmark) to explain the pension funds' performance—I run regressions for each PFA and for different fund groups against the benchmark. I group funds to determine whether the results of individual funds are different from those of fund groups and whether some funds exhibit similar characteristics in different periods of time. I divide the pension funds into six subsets to find out whether fund size, financial crises, and number of competitors in the market provide different results. This division into groups is especially useful to detect whether leaders, survivors, acquirers, and defunct funds exhibit similarities or differences in asset allocation:[21]

[21] In this document, the benchmark is the weighted average return defined in the law. However, Hensel, Ezra, and Ilkiw (1991) propose "the average of what everybody is holding" as benchmark portfolio for U.S. pension funds.

Group 1 = the three largest funds.

Group 2 = the two medium funds.

Group 3 = the two smallest funds.

Group 4 = the seven funds that survived to 2001 (from the 13 existing in 1997).

Group 5 = the three funds that acquired other institutions and survived.

Group 6 = the six funds that were acquired and did not survive.[22]

To test how much the variability of group return, expressed by R-squared, is due to the benchmark, I analyze Groups 1, 2, 3, 4, and 5 for the whole period (55 months), and I analyze all six groups for the periods corresponding to the Asian and Russian crises and for the period during which only 7 funds remained in the market (2001:02–2001:12). To find out if there are individual differences across funds that I could get rid of by grouping funds into portfolios, I apply the prior methodology to each fund. I regress Model (3.1) for those groups and for individual funds. The dependent variable is $RetPFA_{(i,t)}$, return of both individual funds and funds group (i) during time (t). The independent variable is the weighted average return, $RetBenchmark_{(t)}$.

(3.1) $\mathrm{Re}tPFA_{i,t} = \alpha_i + \beta_i * \mathrm{Re}tBenchmark_t + \varepsilon_{i,t}$

i = individual funds (1,2…13) and funds group (1,..6), t = period 1,..55

Table 3.2 reports the outcomes of this model in Panels A and B. When the regression is run for each individual fund for the period 1997:06–1998:06, the R^2 varies between 0.96 and 1.0 with an average of 0.99 and standard deviation of 0.009.[23] The average beta coefficient is 1.00 with a standard deviation of 0.044. In regressions that include individual survivor funds for the period 1997:06–2001:12, the average R^2 is 0.99

[22] Most of the acquisitions took place between 1998:05 and 1999:09.
[23] All thirteen PFAs existed then; mergers started later.

with a standard deviation of 0.004, and the average beta coefficient is 1.01 with a standard deviation of 0.042. From these values, with both beta coefficients equal to 1.0, on average, and with a tiny volatility, I infer not only that an individual PFA return is explained by the benchmark but also that each PFA replicates the investment strategy of the benchmark, which is equivalent to arguing that each PFA's plan is what other funds are doing.

With respect to fund groups, in the regressions run for different periods, the benchmark that is statistically significant at 1 percent explains more than 99.0 percent of return variability of pension funds. In particular, the R-squared of Group 1 is 99.3 percent; Group 2, 99.8 percent; Group 3, 98.9 percent; Group 4, 99.3 percent; Group 5, 99.0 percent; and finally, Group 6, 99.0 percent.[24] Likewise, there is no difference in how much of the return variability is explained by the benchmark among PFAs for different periods. The beta coefficients range between 0.99 and 1.06, all of them being statistically significant.

I test the hypothesis that the beta coefficient is different from 1.0 by running cross-sectional regression and computing time series coefficients for different periods of 1-month, 2-month and 3-month returns. The results do not reject the null hypothesis that beta is equal to 1.0. This evidence is suggestive of PFAs that may be tracking the market portfolio (benchmark) defined as weighted average return, with beta equal to 1.0. When the model is regressed using the simple average return as the benchmark, the results are similar to those of Table 3.2. Furthermore, the outcomes for Model (3.1) with the simple average return as independent variable are not different from those of the weighted average and are not shown. These results provide evidence that although the number of

[24] In a seminal paper, Brinson *et al*. (1986) find asset allocation explains 93 percent of the variability in U.S. pension funds. Brinson *et al*. (1991) obtain a value of 91 percent, and Ibbotson and Kaplan (2000) provide evidence that asset allocation explains 91 percent and 87 percent of the return variability of U.S. pension funds and mutual funds, respectively.

pension funds decreased and the stock market bore two external shocks, the benchmark still continues explaining, to a great extent, the return performance of all pension funds.

In relation to the second question, I run Model (3.2) to determine the how different fund managers allocate the clients' money. The dependent variable is premium in return for each PFA (i) at time (t) defined as ReturnPFA $(_{i,t})$ minus ReturnBenchmark$(_t)$, which corresponds to excess returns of each fund over the benchmark; and five independent variables, called premium in asset allocation, are characterized by the expression WeightPFA$_{i,t-1,a}$ minus WeightBenchmark$_{,t-1,a}$. It corresponds to the difference between the share of asset allocation of each pension fund (i) (i=1,..13) and that of benchmark for each asset class (a =1,..5) at month (t) (t=1,…55 months).[25]

(3.2)

$$[RetPFA_{i,t} - RetBenchmark_t] = \sum_{a=1}^{5} \beta_{i,a}[WeightPFA_{i,t-1,a} - WeightBenchmark_{t-1,a}] + \varepsilon_i$$

What I postulate is that the coefficients of asset allocation in Model (3.2) are equal among pension funds, i.e. $H_0 : \beta^{PFA(i)}_{asset(a)} - \beta^{PFA(j)}_{asset(a)} = 0 \ \ with\, i \neq j$. The null hypothesis is tested under four different data categorizations: (i) individual PFA against the rest of the existing group, (ii) pair of PFAs involved in mergers, (iii) different periods and, (iv) individual PFA within its group size. To test that, I use the Chow Test based on the sum of squared errors (SSE).[26] The procedure that I apply rests on three steps. First, Model (3.2) is regressed for a specific pension fund, PFA(i), computing SSE1; second, the

[25] The asset allocation defined above is stocks, bonds, banking deposits, foreign assets, and mortgage-backed securities. On a monthly basis, I compute the difference between the weight of each asset within the asset allocation used by each AFP and the weights of a benchmark obtained from the average of the industry asset allocation weighted by the asset values.

[26] The usefulness of this lies in testing whether there has been a change in the parameters from one group to another. Greene (2000) describes it as a test of structural change if regression coefficients are different in the distinct subsets. $Chow\,Test = \dfrac{(\varepsilon\varepsilon_T - \varepsilon\varepsilon_1 - \varepsilon\varepsilon_2)/k}{(\varepsilon\varepsilon_1 + \varepsilon\varepsilon_2)/(n_1 + n_2 - 2k)}$

regression is run for the remaining existing funds as a group, PFA($i \neq j$) getting SSE2; and third, SST (sum of total errors) is obtained by running the regression for all existing PFAs. Due to the series of acquisitions, I evaluate the existing funds up to the date of each acquisition. For the first acquisition, the evaluation period is 1997:06–1998:05 with thirteen existing PFAs. For the second acquisition, the analysis time is 1997:06–1998:08 with twelve existing PFAs. At the end, the seven surviving funds are evaluated from 1997:06 to 2001:12.

In addition to Model (3.2), I also use two more regressions to evaluate the robustness of the results by testing the same hypothesis. The two additional models are:

(3.3) $$(3)\ Return_{i,t} = \alpha + \sum_{a=1}^{4} \beta_{i,a}[AssetWeightPFA_{i,t-1,a}] + \varepsilon_i$$

AssetWeightPFA($_{i,t-1,a}$) corresponds to the asset allocation weight of PFA(i = 1,2..13), at time (t = 1..55 months) and the assets group (a = 1,2,3 and 4).

(3.4) $$(4)\ [RetPFA_{i,t} - RetAverage_t] = \sum_{a=1}^{5} \beta_{i,a}[WeightPFA_{i,t-1,a} - WeightAverage_{t-1,a}] + \varepsilon_i$$

The return premium is defined in Model (3.4) as the simple average across funds and is regressed against the weight premium defined as the difference between the weight of asset allocation of each PFA and the simple average asset allocation weight, for the PFA (i =1,2..13), at time (t = 1..55 months) and the assets group (a =1..5). Models (3.2) and (3.4) are expressed in deviation form as a way to get rid of the multicollinearity problems and hence, no intercept is needed. The summation of the five asset allocation weights for each fund is equal to 1.0. Other mechanism used to eliminate multicollinearity problems is to drop one variable and I use Model (3) with intercept and four asset allocation weights (a=1,2,3,4). The alternative for not dropping one weight is to use a variable that is realized by subtracting the benchmark's asset allocation weight from each fund in Models (3.2) and (3.4).[27]

Table 3.3 describes the both Chow test and F-Test significance values in five panels. Most of F-test values are non-significant at 10 percent. From Table 3.3–Panels A-1 and A-2 that use Models (3.2) and (3.3), it is appreciated that the Chow test values tend to fail to reject the null hypothesis in several individual funds. The statistical results lean toward supporting the idea that pension funds are inclined to hold the same asset allocation. In Table 3.3–Panel C, Model (3.2) is used and the data are grouped in fund pairs involved in acquisitions. The sum of squared errors is computed for each pair as a group, i.e., acquiring-acquired funds. The statistical analysis shows that beta coefficients are equal among fund pairs. None of the F-values is significant at least at 10 percent.

Table 3.3–Panel D builds its results on Model (3.4) by putting together only the seven pension funds present during the entire period. Results show that the highest significant value is at 3.9 percent. When different periods are analyzed, the asset allocation (one-year period) using Model (3.2), Table 3.3–Panel E shows there are no significant changes in asset allocation among the funds group through time. In fact, even though the Chilean financial market fell in 1997:06–1998:01 and in 1998:08 (due to the effects of the Asian and Russian market crises, respectively), the statistical outcomes still support the hypothesis of no differences in asset allocation.

Table 3.3–Panel F uses Model (3.4), premium in return and premium in weight relative to industry average. The sample is classified in three groups by asset values size—the three largest, the two medium funds, and the two smallest funds—and the total sum of squared errors are computed within each group. Similar to the above findings, the observed F-values demonstrate that there is no statistical significant difference among

[27] Suits (1984) argues in favor of transforming the variable rather than dropping one variable.

funds' asset allocation within funds of equal size. Comparing the findings of Table 3.3–Panels A, B, and C of individual PFAs with those of Table 3.3–Panel F, I infer that funds clustered within the same size category and measured by asset values tend to seem more like each other by replicating their asset allocation.

Both on variability in returns and on differences in allocation under several scenarios and within different groups, the evidence suggests that the investment decisions of Chilean pension funds behave as one group by copying each other's asset allocations, and that the weighted average portfolio of what all funds are holding has become the benchmark for all PFAs.

This evidence suggests that the regulation is having a profound impact on the behavior of Chilean PFAs. Specifically, it appears that without the MGR, PFAs would perform differently. A reasonable interpretation of the evidence is that fund managers' returns are similar because they mimic each other's asset allocation and asset selection in order to avoid being penalized by not achieving the MGR. Consistent with this interpretation, one can observe that in the Chilean mutual fund industry, there is no MGR requirement, and mutual funds show a variety of returns. Unlike pension funds, Chilean mutual funds have systematically grown in new funds and institutions (families).[28] Mutual fund managers allocate their money independently of what other fund managers do. Specifically, Walker and Maturana (1999) test the hypothesis that mutual fund management fees are high and mutual fund returns are low. They report that the average return in the period 1990–1997 of stock mutual funds is 13.1 percent and that there are differences of over 10 percent in performance across funds. In their evaluation of the stock mutual fund performance, Walker and Maturana find that Jensen's alpha is non-

[28] In *Overview of Chilean Mutual Funds* (2001), the Superintendence of Securities and Insurance reveals that the number of funds grew from 115 to 177 and the number of fund families increased from 14 to 17 between 1999 and 2001.

signficant. They conclude that stock mutual fund performance before fees tends to be similar to passive strategies despite this industry having increased in the number of funds.

3.3.2. Correlations and Granger Causality

To understand more deeply the mechanism used by pension funds to exhibit similar asset allocation, I study whether there is any pension fund that triggers the reaction of others when selecting or trading assets. In other words, who moves first? Granger (1969) proposes a procedure to examine a causal relation between two variables. The causality effect arises when the result of PFA(Y) is better explained taking into account PFA (Y)'s information and PFA(X)'s. Strictly speaking, causality is referred to $\sigma_{\varepsilon}^{2}(Y \mid I) > \sigma_{\varepsilon}^{2}(Y \mid I, X)$ being σ_{ε}^{2} the variance of errors series. Formally, I follow Definition 4 in Granger (1969), namely, "causality lag." Causality lag is more appropriate to this sample because fund Y may make better decisions based on the previous investment decision made by fund X. The number of lags is useful to understand how spontaneous funds delay in reacting to information of other funds' choices. Hamilton (1994) also specifies an econometric test for Granger causality starting from an autoregressive model of p lags for both Y and X variables, the null hypothesis being that beta coefficients of the variable X are equal to zero,[29]

$$H_0 : \beta_1 = \beta_2 = \ldots \beta_p = 0$$

Before dealing with regressions, I compute the correlation matrix of both weights and changes in weight of the asset allocation across pension funds. I list in Table 3.4 the correlation matrices of portfolio holding of each PFA against the benchmark's, separated in three asset classes; domestic stocks, fixed income securities, domestic stocks and foreign assets. There exists a high and almost perfect positive correlation in each PFA's

[29] Formally, $Y_t = \alpha_0 + \alpha_1 Y_{t-1} + \ldots \alpha_p Y_{t-p} + \beta_1 X_{t-1} + \ldots \beta_p X_{t-p} + \varepsilon_t$

asset class with respect to the benchmark's. Table 3.4–Panel A shows a strong correlation in fixed income securities (between 1.0 and 0.93), domestic shares (between 1.0 and 0.97) and foreign assets (between 0.63 and 0.98). Fixed income securities and domestic stocks account for over 90 percent of total asset values of PFAs. When fixed income securities are decomposed in five assets, Table 3.4–Panel B shows positive as well as negative correlations among this assets group. Considering these findings, I interpret that pension funds behave differently among individual fixed income securities but keep total fixed income weights as close as possible to that of the industry. As most of these assets are allocated in categories AAA and AA, each security may be seen as a substitute within this group, since their returns are very similar, which would allow PFAs not to deviate significantly from the average of the system regardless of the asset selection in fixed income securities.

Table 3.4–Panels C through F present the correlation of weights and changes in weights for domestic stocks and domestic bonds. In the case of stocks, the correlation of weights ranges between 94 percent and 99 percent for both periods, and that of changes in weights varies between 67 percent and 97 percent. Bonds show no specific pattern and exhibit positive and negative correlations. From these findings, I infer that pension funds follow the same investment model in variable-income securities but not in fixed-income securities.

With regard to the cutback in the stock weight from 31 percent to 10 percent during the whole period, funds tend to mimic the stock weight in the asset allocation by investing their free resources in any fixed-income asset since domestic and foreign bonds, banking deposits, and mortgage-backed securities are almost perfect substitutes in return. One possible reason for PFAs reducing their stock weight through the period is that the Chilean stock market plunged during the Asian and Russian crises, generating negative returns of 28 percent and 30 percent, respectively. Additionally, some criticism arose from political sectors on the PFAs' ability to protect saving accounts from adverse financial impacts and on the excessive allocation in stocks. What in fact happened was all PFAs shrank their domestic stock weight.

Before applying the Granger test, I group the data according to (i) fund size, (ii) fund pairs, and (iii) date of acquisition. The dependent variable is the change in stock weight in a PFA(i).[30] The null hypothesis is "variable X does not Granger-cause Y" i.e., beta coefficients of X are equal to zero, $Ho: \beta_1 = \beta_2 = ...\beta_p = 0$.

The three feasible independent variables that I consider are the change in stock weight of (i) the benchmark, (ii) the three leaders and, (iii) any other PFA (i≠j) that may explain Granger causality. The investigation selects fund by fund in order to determine specifically who is following whom. The hypothesis tilts to look at evidence that the larger funds' strategy is copied by smaller pension funds, keeping in mind that the Minimum Guaranteed Return (MGR) is computed giving greater importance to larger funds. Hence, I claim that fund managers pay more attention to variable income securities rather than other assets to avoid fluctuating away the floor return by following either industry average stock weight or the three largest funds.

Panel A of Table 3.5 condenses the statistical evidence of the Granger causality test of those pension funds that were initially absorbed by larger funds. What compels consideration of this group is that its investment strategy is Granger-caused by either the three leaders or the weighted average portfolio with just a 1-lag period, at less than 1 percent of significance. Results show that these PFAs behave as followers of the leaders'

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[30] The correlation of *stock weights* with the *benchmark* (described in Table 3.4) is higher than that of *changes in stock weights*. However, I evaluated *changes in stock weights* because it better illustrates the causality effect when I rotate the independent and dependent variables. This occurs because *stock weights* reflect ending position but not changes. When regressions are run, I exchange the dependent and independent variables to check causality; these results are presented in Table 3.5 in the last row of each PFA.

moves. In fact, they adjust their stock weight almost instantaneously when driven by the leaders' or the benchmark's moves. Five out of six funds keep a close watch on the three leaders or weighted average stock weight when evaluating their investment decisions. For instance, PFA Aporta, which remained functioning longer than the others (43 periods) apparently tends to mimic the strategy of the three leaders; however, when the leader group is broadened, it tracks what PFA Cuprum does with 2-lags.

To check these results, I exchange the dependent variable for the independent one to discover any causality issue between the variables, i.e., I run the regression for each PFA "X depends on past X and Y" with the null hypothesis "variable Y does not Granger-cause X." Nonetheless, the hypothesis is not rejected in any case, proving the one-way direction of the variables. On the other hand, Table 3.5–Panel B documents the information of the existing PFAs ranked by size from the largest to the smallest. The statistical evidence strongly indicates that the three leaders move first and then the medium and small funds follow their strategies with a 5-lag period. In the case of the largest funds, PFA Provida is Granger-caused by the weighted average, but I discard this alternative due to its weight is doubled count on this average.[31] A better explanation is that the other two large funds Granger-cause PFA Provida with eight lags. Similarly, the other two leaders are Granger-caused by the combination of allocations of the leaders with seven lags. In the case of medium funds, the test is more accurate. PFA Summa's stock allocation is explained significantly by PFA Cuprum's with five lags. PFA SantaMaria's result is driven by PFA Habitat's strategy. In the case of the two small funds, PFA Planvital is enlightened by the two largest funds, and PFA Magister is Granger-caused by PFA Cuprum with seven lags. In light of above findings, I conclude

[31] In other words, I dismiss the importance of this indicator (*weighted average*) because I would double count the weight of the largest fund in the Granger causality autoregressive equation, so that the answer lies on the other two leaders.

that asset allocation among funds is heavily determined by their relative size in the system.

To summarize, the large funds' investment strategy seems to be mimicked by others of equal size with seven lags. The medium and small funds are significantly inclined to be followers of strategies pursued by one or two large funds with five lags. The merged PFAs surfed on either the weighted average or leader allocations with just a 1-lag period.

3.3.3. On Stock Trading Activity

Taking into account the previous evidence that stock weights exhibit high positive correlation, I study in more detail how pension funds trade their stock holdings, I apply the methodology of herding defined in the seminal document by Lakonishok, Shleifer, and Vishny (LSV) (1992) and utilized subsequently by Grinblatt, Titman, and Wermer (GTW) (1995), Choe, Boe, and Stulz (1999), Wermers (1999), and Lobao and Serra (2003). In addition, I use Sias (2004)'s approach to evaluate whether stock selection of fund (i) is driven mainly by past fund (i)'s decisions or by other funds's.

Conceptually speaking, herding arises when a fund manager's knowledge about others' decisions not only changes his investment decision but also reveals information that he does not have currently. More explicitly, Scharfstein and Stein (1990) develop the idea of the reputation effect in which herding is a solution for managers when they reach unprofitable returns. When managers make the same mistakes as each other, their performance is not judged badly—in other words, they share the blame. Bikhchandani and Sharma (2001) explain that one of three reasons to herd is that fund managers' compensation is rewarded by imitation.[32] In this setting, PFA managers worry about

[32] In the extensive literature of herding is Banerjee (1992), Bikhchandani et al. (1992), Devenon and Welch (1996), Hirshleifer and Teoh (2003). Also, a new herding approach is found in Sias (2004).

their reputation and compensation with respect to being punished for falling below the MGR floor since they are assessed relative to their peers' performance and the benchmark.

To explore the notion fund managers copy their stock trading, Model (3.5) follows the methodology of LSV (1992) to measure the herding behavior. $H(i,t)$ is the herding measure for the stock (i) in the month (t). Herding refers to the tendency to buy (sell) a certain stock by a group of funds at certain period. This occurs when the proportion of buyers, $p(i,t)$, of a stock is above the expected proportion of funds, $\overline{p}(t)$, that buy stocks in the market in the month (t).

(3.5) $H(i,t) = \left| p(i,t) - \overline{p}(t) \right| - AF(i,t)$ where,

$$p(i,t) = \frac{B(i,t)}{B(i,t) + S(i,t)}$$

$$AF(i,t) = E \mid p(i,t) - E[p(i,t)] \mid$$

The adjustment factor, $AF(i,t)$, appears in Model (3.5) to take into account the possibility of random variation of $p(i,t)$ around $\overline{p}(t)$ under the null hypothesis of independent transactions among funds, i.e., no herding. $S(i,t)$ is the number of sellers in the market for the stock (i) and in the month (t). The number of buyers, $B(i,t)$, has a binomial distribution with parameter $p = \overline{p}(t)$. The term $\overline{p}(t)$ is the proxy of $E[p(i,t)]$ under the null hypothesis and constant for all stocks during a month, but changes over time. The null hypothesis establishes that there is not herding if the current proportion of buyers equals the expected value for all stocks and is constant equivalent to $\overline{p}(t)$ for a certain month.

Intuitively, this measure has two components and works in the following sense. For a particular stock-month, the difference between the proportion of traders buying this stock and the monthly average of the proportion of buyers denotes a purchasing trend beyond the market's. In the presence of a bearish market, in general both numbers would tend to be equal, meaning there is no herding. However, if, in a bearish market, a particular stock exhibits a higher proportion of buyers, it means some traders are taking a long position and would herd among them. The second component is the adjustment factor. The model considers two types of traders (buyers-sellers) and each month, a binomial distribution is computed on the likelihood of observing a certain number of buyers given the probability of occurrence equal to p(t). The reason for including this adjustment factor is to account for bias that would occur if stocks were traded by a few investors. The null hypothesis states that if herding does not exist, the proportion of buyers has the same expected value for all stocks in a given period and is constant equal to $\overline{p}(t)$. Any deviation from $|\, p(i,t) - \overline{p}(t)\,|$ above the expected $AF(i,t)$ is evidence of herding. If this difference is equal to or inferior to zero, that means there is no herding. The greater the number of buyers trading a stock (i,t), the higher the herding value, ceteris paribus $\overline{p}(t)$.

This herding appraisal allows differentiating spurious herding from intentional herding as pointed out by Bikhchandani and Sharma (2001). The advantage of Model (5) lies in the fact that if a large group of funds decreases their holdings in stocks—for example, in a bearish market—and a small group comes up buying stocks, then most of the funds that followed the market trend are not under a herding effect, but the small group is.

To complete this analysis, I use Sias's (2004) herding measure. Sias examines institutional trading activity by analyzing cross-sectional correlation between demand for a security (k) last quarter and demand for the security (k) this quarter. Unlike LSV (1992) approach, Sias (2004) method captures the effect that traders may follow their own pattern or other's over adjacent periods. He determines institution's position of each security (k) as a fraction of the security's share outstanding per quarter. Investors are classified as buyers (sellers) if their ownership in stock increases (decreases) and defines:

$$Raw\Delta_{k,t} = \frac{Buyers_{k,t}}{Buyers_{k,t} + Sellers_{k,t}} \qquad k = stock$$

The standardized fraction of institutions buying security (k) in quarter (t) is:

$$\Delta_{k,t} = \frac{Raw\Delta_{k,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{k,t})} = \frac{P_{i,t} - \overline{P}_t}{\sigma(P_{i,t})}$$

Sias (2004) runs a cross-sectional regression of the standardized fraction of institutions buying security k:

(3.6) $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$

He argues that this correlation has two components: (i) correlation may arise from individual investors following themselves and (ii) correlation may result from investors following each other (herding) over adjacent quarters. However, he proves (in his appendix) that the correlation between current quarter investors buying and lag quarter's investors computed from N investors across K securities can be decomposed into:

(3.7) $$\beta_{k,t} = \rho(\Delta_{k,t}, \Delta_{k,t-1}) =$$

$$\left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] * \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{n,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right] +$$

$$\left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] * \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}} \sum_{m=1, m\neq n}^{N_{k,t-1}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right]$$

I run the models (3.6) and (3.7) to determine the beta coefficient and its decomposition. However, to apply these models, it is necessary that PFA (i) have traded the same stock in at least two consecutive periods. Due to all funds having their stock holdings decrease, this measure presents some limitations in its application on the sample. In several months, PFAs mainly sold stock positions, and a few of them bought but not in consecutives periods, restricting the use of the Model (3.7).

3.4. HERDING BEHAVIOR

3.4.1. Herding on Trading Activity

In the Chilean Stock Exchange, there are 330 publicly owned stocks listed. According to the Risk Rating Commission, pension funds are allowed to invest in less than 50 percent of these stocks. In the sample, pension funds hold in their portfolio, on average, 120 domestic stocks concentrated in large market capitalization stocks.

For each month, I classify the stocks in (i) market value quintiles, (ii) return quintiles, and (iii) ownership concentration quintiles, and I determine the number of traders per stock (i,t), being i =1,2….125 stocks and t =1,2…55 periods and the herding value. This measure provides 3,052 observations, of which only 1,312 are positive and valid.[33] To analyze these numbers, I require the condition of regarding at least two funds trading a given stock-month to be considered as herding.

The results show a herding level with a mean of 1.8 percent (highly significant with a t-value of 5.40). Comparatively, LSV (1992) claim that their herding value of 2.7 percent is relatively small to indicate herding in a broad sense. Similarly, GTW (1995) argue that their herding measure of 2.5 percent weakly supports herding behavior, and Wermers (1999) verifies a herding of 3.4 percent in mutual funds. Despite the small herding mean value, Panel A of Table 3.6 draws attention, illustrating that the herding value in pension funds undoubtedly rises with the number of trading funds; that is, funds trade the same stock-month more often when they see others doing so.

From Table 3.6–Panel B, it is noted that the larger the number of funds trading, the greater the herding mean. The herding mean climbs to over 18 percent when there are

[33] I adjust for takeovers occurred in the stock market in 2001 and that obligated to pension funds to sell their holdings in some stocks. The stocks that disappeared of PFA holdings were Chilgener, Chilquinta and LabChile.

ten pension funds trading in the same stock-month direction. The highest reported value skyrockets up to 34.5 percent when there are thirteen funds involved in trading activities. As referenced, Wermers (1999) and LSV (1992) find values as high as 2.7 percent and 3.6 percent respectively when the number of traders increases. The Chilean pension funds show evidence of a larger herding mean before the acquisition of funds when there were more funds trading.[34]

However, Sias (2004) in his document finds a beta coefficient of 11 percent, which is explained equally by both trades. Using this approach in PFAs, Table 3.7 shows that on average, the beta coefficient is 34 percent. Therefore, the data once again suggest that PFAs herd significantly. The main reason for this result is that fund managers tend to follow others' trades, i.e., the investment strategy in domestic stocks of PFA (i) is driven by PFA's (j) with (i≠j). This evidence is consistent with previous Granger causality findings.

3.4.2. Herding in Different Periods

In the period under analysis, I encounter several important events that allow a closer look at the herding behavior of pension funds. These include two financial crises—the Asian "flu" in the period 1997:06–1998:01 and the Russian crisis in 1998:08 that hit the Chilean Stock Exchange strongly—and changes in regulations such as the amendment that modified the way of calculating the MGR in 1999:10.

3.4.2.1. Financial Crises

The most precipitous drops of the Chilean Stock Exchange occurred in 1998:01 and 1998:08, at 12 percent and 30 percent respectively. The Asian crisis lasted 8 months,

[34] Lobao and Serra (2003) also describe a similar tendency in Portuguese mutual funds, and with a herding value of 11.3 percent. In contrast, Wermers (1999) shows that the herding level decreases with the increase in trading activity of mutual funds (when 50 or more mutual funds trade over 274).

and the Russian crisis just 1 month. From Panel A in Table 3.8, no herding activity can be seen in the month of the Russian fall. In a bearish market, if most agents follow the market trend, then the herding value for several stocks tends to be zero; however, if a group of agents is involved in buying the stock (i), then the herding value is going to be positive for that stock. Despite the high correlation in stock trading activity during financial crises, herding values are relatively small or zero, as documented by Choe et al. (1999) in the Korean market. In particular, the Chilean stock market plunged 28 percent during the month of the Russian crisis. In that month, the herding measure is negligible because PFAs uniformly reduced their holdings in stocks. In the next month, the herding value is positive. The lowest correlation across funds on changes in stock weights for the 3-month period of one month before (t-1) and one month after (t+1) the Russian crisis (t) is 0.99, but three months after this window (t+2, t+4), it is 0.90.

The LSV (1992) herding measurement allows capturing the effect of spurious herding when institutions not only react together to the same information but also assess fundamentals in the same direction. However, this figure is completely different during the Asian crisis period. To examine in particular this crisis, this study takes into account two sub-periods, 1998:01 (the deeper stock market fall) and 1997:06–1998:01, adding the criterion of observing different numbers (N) of funds trading at the same time, with N>1 and N>5. I document a herding mean of 7.43 percent for the period 1997:06–1998:01, which is considerably higher and statistically more significant than that of 1998:01 (3.46 percent) when N>5. When N>1, herding levels in both sub-periods tend to be very similar. To explain this difference, I separate the trading activity in buyer and seller positions. As described before, in a bearish market I would expect to view that a large herding mean comes from net buyer positions. The greatest herding values arise when effectively more buyers than sellers are trading. With 35 percent of these observations corresponding to the number of buying funds greater than the number of selling funds, the herding mean is 18.7 percent (at 1 percent of significance). When the number of sellers is equal to the number of buyers (12 percent of observations), there is no evidence of herding. With the remaining 53 percent of observations, I document a slight herding value of 2.1 percent.[35] One possible explanation for the existence of herding during the Asian but not the Russian crisis is that the uncertainty of the duration of a crisis has tended to make herding activity more plausible as a mechanism of protection in favor of the MGR.[36] One month is just 1/12 of the MGR evaluation period, and the Asian crisis period represents 8/12 of the year. Fund managers are more concerned about the danger of deviating from the herd in their stock selection, and so are evidently inclined in mimicking what other managers are doing in a longer financial crisis.

3.4.2.2. Changes in MGR Regulations

In October of 1999, the SPFA enacted an amendment whose aim was to extend the MGR appraisal period from the past 12 months to the past 36 months. The main objective pursued by the government was to remove the uncertainty in returns due to the short MGR period and two stock market crises. However, I would expect that fund managers continue watching each other to make their investment decisions because the penalty of deviating from the MGR still remains in the system. Probably, at the beginning of this amendment, managers could diverge in asset allocation and selection, but within 36 months, they would come back to replicate their previous investment style. In order to evaluate whether the effects of this change (the extension of the MGR

[35] In the case of N>1, 26 percent of observations (buyers > sellers) brings about a herding mean of 14.5 percent; 18 percent (buyers equal to sellers) does not account for herding; and the remaining (buyers < sellers) produces 3.5 percent. When I say “no” herding, it does not mean the value is zero, but either zero or negative. Herding refers only to positive values. When N>1 and N>5, the weighted average of the herding level is computed using the negative values as well.

[36] In contrast, Choe, Boe and Stulz (1999) examine the behavior of foreign investors in the South Korean market during 1996-1997 and find no support for a herding level during the Korean financial crisis.

evaluation period) altered to some extent the trading behavior among funds, I divide the sample into four periods, 1997:06–1998:07, 1998:09–1999:10, 1999:11–2000:11, and 2000:12–2001:12. The months of the two greatest falls in the stock market are removed as a way of shrinking the volatility by shocks.[37] The scenario base under this analysis is the period 1998:09–1999:10; the amendment was in force during the following two years. I separate once more the sample by number of funds trading at each time such as N>1, N>2, and N>3.

Panel B of Table 3.8 reveals a U-shape in the herding value when there are at least two or three funds trading at the same time. With N>2 (N>3), the base period illustrates a herding level of 1.8 percent (2.5 percent), which decreases to 0.9 percent (1.9 percent) in the following period, but later rises to 3.3 percent (4.0 percent). If the information is observed with N>1, the outcomes show that the herding level increases in the two subsequent periods from 0.3 percent to 1.4 percent and 1.5 percent respectively. In light of this evidence, it appears that the amendment had an impact on herding activity but its effect was ephemeral.[38] Pension funds came back to herd a year after the amendment was enacted.

3.4.3. Herding in Stocks with Different Characteristics

In this section, I explore what kinds of stocks experience more herding. To do so, the stock sample is divided into quintiles of market capitalization (size) and in economic sectors. The idea is to find out whether PFAs are predisposed to herd more (a) in small market capitalization stocks as documented by Wermers (1999) and LSV (1992) or (b) in

[37] The dates are 1998:01 and 1998:08. In any case, this information does not affect results because the relevant comparison lies on dates starting from 1998:09, one year before the amendment, up to 2001:12. The initial period 1997:06–1998:07 is shown so readers can keep in mind the whole cycle.

[38] In unreported results, when the number of traders used equals N>3, N>4, and N>5, the evidence continues being a U shape.

large market capitalization stocks, considering that a great proportion of the stock holdings are concentrated in this kind of stocks.

3.4.3.1. Market Capitalization Stocks

I compute the market capitalization of each stock (i) and classify them in quintiles, the largest being (Q1) and the smallest (Q5). In each period, I change the quintiles' composition on the basis of fluctuation experienced in market capitalization. In 1997:06, pension funds, on average, held 125 stocks in their portfolios but at the end of the sample period, 2001:12, this number fell to 95. In the same way, the stock weight in asset allocation shrank from 30 percent to 10 percent. Most empirical studies of herding show evidence of more trading activity in larger stocks but with a lower herding level. LSV (1992) and Wermers (1999) find that smaller stocks exhibit considerably higher herding values than larger stocks. Nevertheless, findings in Panel A of Table 3.9 show that higher herding values correspond to the largest quintile (Q1) and the smallest quintile (Q5), being highly significant at 1 percent. With the number of traders greater than 1 (N>1), herding levels per quintile are 2.9 percent (Q1) and 5.9 percent (Q5). The trend is almost the same when there are more than three funds trading except that the herding means jumps to 4.1 percent and 9.2 percent respectively. These results are also are consistent with those of Sias's (2004) measure illustrated in Table 3.7. Herding values significantly increase when PFAs trade stocks classified in the Q1 and when there are more PFAs trading stocks in the same direction. The results of herding in large market capitalization stocks are consistent with the incentives that regulation produces on fund managers. PFAs have to herd in large stocks to keep their portfolio close to the benchmark. If one fund does not follow the same strategy in these stocks, its performance would deviate from the benchmark return, but if it does not herd in the small capitalization stocks, its performance would not diverge significantly from the benchmark because this group of stock accounts for less 5 percent of stock holdings.

3.4.3.2. Economic Sectors

I account for sixteen business sectors and show in Panel B of Table 3.9 just eight sectors that comprise each one at least 10 percent of observations and with numbers of traders of N>1 and N>3. I discard the other eight sectors because of their small importance relative to the first eight sectors. The largest and most significant herding values under LSV (1992) correspond to areas of power plants (4.4 percent), food and beverages (3.4 percent) and telecommunications (3.0 percent). Not much herding activity is seen in either retailers (department stores, supermarkets) or banking segments. The other sectors not listed in Table 3.9–Panel B exhibit irrelevant or no herding values. To greater extent, I examine mainly the largest two stocks corresponding to each economic segment and find that larger stocks related to three economic sectors—power plants, food and beverages, and telecommunications—are preferred by PFAs to herd. Most of their herding levels, reported in Table 3.9–Panel C, are statistically significant and fluctuate between 2.9 percent and 6.8 percent with N>1. The herding values range between 2.1 percent and 9.1 percent when there are at least three funds trading (N>3).

3.4.4. Additional Tests on the Determinants of Herding

Aside from herding values, what is more remarkable to know is when it is more likely to see pension funds herd. The procedure I apply to statistically response the question is to (i) rank stocks from the larger market cap to the smaller one and group them in bundles of five or ten shares, and (ii) regress a Tobit model with a right-censored dependent variable, Herd*, herding value per stock, to be greater than zero. The model defined in Model (3.8) is useful when the dependent variable is limited to certain values.

The independent variables are StockSize (as a variable for the larger five, ten stocks and so on) and NumberTraders both from N>1 to N>10 and with ranges as 2≤N≤3, 4≤N≤5).[39] Econometrically speaking, I cannot use an OLS regression because the relevant herding values are only the positive ones. The solution is to use a Tobit model (maximum likelihood estimation) that provides the probability of reaching an observation beyond zero.

$$\begin{aligned} &Herd_i^* = \alpha + \beta_1(StockSize_i) + \beta_2(NumberTraders_i) + \varepsilon_i \\ (3.8)\quad &Herd_i = 0 \quad if \quad Herd_i^* \le 0 \\ &Herd_i = Herd_i^* \quad if \quad Herd_i^* > 0 \end{aligned}$$

In Table 3.10, I report the values of censored regression models. The first censored-data regression run is considering quintiles:

(3.9) $Herd_i^* = \alpha + \beta_1 Q1 + \beta_2 Q2 + \beta_3 Q4 + \beta_4 Q5 + \varepsilon$ where Qi = Quintile (i), i=1,2,4 and 5

Table 3.10 -Panel A's result shows that the constant (α) and the β_1 are the unique statistically significant coefficients. The positive sign of Q1 (the largest market cap) is econometrically correct. Quintile Q5 (the smallest market cap) is no longer a valid explanatory variable due to its negative sign and non-significance. Panel A also indicates the probability that {Herd*| Q(i)} will be observed in a herding interval.[40] The likelihood of observing herding in the range 0.0<Herd*< 0.05 given Q1 occurs is 17.5 percent. The chances decrease slightly for higher herding values. The outcome of Model (3.10) is listed in Table 3.10 -Panel B. The independent variable is NumberTraders trading stock (i) at month (t):

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[39] I consider the variable *StockSize* with different meanings. It is used as a dummy for the variable *Rank1_5*: the largest 5 stocks or *Rank6_10*: the following 5 largest stocks and so on. Also, the market cap quintiles are referred to as part of this variable. Likewise, *NumberTraders* means number of traders greater than X or number of pension funds trading between X and Y. In addition, some interaction variables are used. In any case, in Table 3.10, I specify the "real name" of used variables as regressors.

[40] It is the probability that the linear prediction lies in the range (a,b), i.e., $Prob(a < X_j\beta + \varepsilon_j < b)$. Regression (7) generates a Likelihood Ratio = 21.4 which is significant at 1 percent.

$$(3.10)\quad \begin{aligned} Herd_i^* &= \alpha + \beta_1(2 \le Trader \le 3) + \beta_2(4 \le Trader \le 5) + \beta_3(6 \le Trader \le 7) + \\ &\beta_4(8 \le Trader \le 11) + \varepsilon_i \end{aligned}$$

Previously, I accounted for herding with number of traders greater than one (N≥2) (Table 3.6). Nevertheless, the picture is to some extent different now. Unlike the first variable 2≤Trader≤3, all of the coefficients are positive and individually statistically significant with a significant Chi-square value at 1 percent. When the number of traders is larger than six (N>6), the probability of seeing funds herding is near 18.0 percent and tends to be stable across herding ranges. In contrast, if there are 4 to 5 traders, the probability decreases in relation to the herding values range. These results are completely expected since the herding measure increasingly rises with more pension funds trading at the same time. Due to this fact, the probability of having 4 to 5 traders trading is inversely proportional to high herding values, which are present when several funds are trading. Perhaps more interesting is to spread out the sample by individual stocks. To regress Model (3.11), stocks are ranked by size (StockSize1_5 includes the 5 largest shares) and put into groups of five and ten shares. What this regression tries to capture is the importance of each group in explaining herding.

$$(3.11)\quad \begin{aligned} Herd_i^* &= \alpha + \beta_1(StockSize1\_5) + \beta_2(StockSize6\_10) + \beta_3(StockSize11\_20) + \\ &\beta_4(StockSize21\_30) + \beta_5(StockSize31\_40) + \beta_6(StockSize41\_80) + \varepsilon_i \end{aligned}$$

Panel C of Table 3.10 strongly supports the evidence that herding is more likely when funds are trading in largest market cap stocks. The chances of finding herding value between 0 percent and 5 percent when trading larger market cap stocks is 55 percent, the highest values provided by the regression for any herding value. Going deeper in the analysis, in Model (3.12), I select the individual stock names that are grouped in StockSize1_10 and StockSize81_more and that belong to quintiles Q1 and Q5 respectively. "β" coefficients are assigned to larger stocks and "γ" coefficients are for smaller stocks. I pick the 5 largest stocks of each group, because they have more observations and are more traded within their own group.

(3.12)

$$\begin{aligned}Herd_i^* = \alpha + \beta_1(Q1\_CTC) + \beta_2(Q1\_Endesa) + \beta_3(Q1\_Enersis) + \beta_4(Q1\_Entel) + \\ \beta_5(Q1\_Cervezas) + \gamma_1(Q5\_Maderas) + \gamma_2(Q5\_Pilmaiq) + \gamma_3(Q5\_Quemchi) + \\ \gamma_4(Q5\_Quilic) + \gamma_5(Q5\_Somela) + \varepsilon_i\end{aligned}$$

Panel D of Table 3.10 shows evidence that not only do larger stocks effectively drive the herding values, but also, statistically, all the beta coefficients but no gamma coefficients are significant.

In unreported results, when a Tobit regression is run using only the 5 largest stocks of the smallest quintile (Q5), none of the regressors is statistically significant. When only the five largest stocks of the largest quintile (Q1) are regressed, their beta coefficients are highly statistically significant and positive. The probability of $0.0 < Herd^* < 0.05$ is similar to 15 percent within this group. All the evidence shown considerably strengthens the assertion that PFAs herd more in the largest stocks because 20 stocks represent a great proportion of the asset selection in stocks and hence may definitively explain the similarities in returns driven by this variable income security. When the hypothesis of differences in returns among PFAs is tested, the statistical evidence does not reject the null hypothesis $Return^{PFA(i)} = Return^{PFA(j)}$.

In sum, it appears that both herding in asset allocation and herding in variable-income securities allow Chilean Pension Funds to achieve the same returns. There exists no real competition in the market in returns, since fund managers of smaller pension funds mimic investment strategies of the three leaders, on average, and the larger funds look among themselves for guidance on what they sell or buy. The pressure on funds managers to herd arises directly from the MGR since it punishes managers who fall below this floor.

3.5. CONCLUDING REMARKS

The current Chilean Pension Funds law, which requires managing institutions to meet a minimum return, offers a natural scenario to understand the investment behavior of fund managers. The minimum guaranteed return (MGR) is computed based on the weighted average of the past-12-months real return across funds, but as of 1999, the assessment period is changed to the past-36-months return. I find that the MGR encourages managers to hold similar portfolios to reach similarities in return.

The mechanism that they use is to copy or herd both asset allocation and stock trading. In relation to asset allocation, there is a 99 percent correlation between the variability in return of individual pension funds and the weighted average return (benchmark), i.e., funds tend to replicate the performance of this kind of "natural" index built from the weighted average portfolio. At the macro level, I document no differences in asset allocation among funds. I am unable to statistically reject the hypothesis that the weight coefficients are equal for each pension fund or for sub-groups of funds. I show evidence of a high positive correlation among funds in changes in stock weights but not in other asset classes. The Granger causality test reports that the PFAs that were acquired by other funds pursued the same strategies as the three leaders or the benchmark with a one-lag period. The three leaders seem to mimic each other.

At the micro level, I study stock trading using the methodologies of Lakonishok et al. (1992) and Sias (2004). Using LSV (1992), I find a herding mean of 1.8 percent. Nevertheless, this value strongly increases to 18 percent when there are more PFAs trading in the market. Under Sias (2004), the correlation between trades of past period and this period of fund (i) is mainly explained by PFA (j)'s trades. Both methodologies show that herding activity increases when PFAs trade in large market cap stocks and when there are more traders in the market. PFAs herd in this group of stocks because the

30 largest market cap stocks account for at least 85 percent of stock holdings. Although the amendment of 1999 extended the evaluation period of the MGR from the past 12 months to the past 36 months, it seemed to decrease herding values for only a short time, because after a year, PFAs increased their herding activity.

The MGR induces fund managers to herd and not to deviate from the benchmark portfolio. The penalty of PFAs diverging from each other, not constraint on investment, is a reason that PFAs realize similar returns. The documented similarity in returns raises two related questions: (i) what makes a client choose one fund over another? and (ii) how do funds compete with each other for customers? These questions and other related issues are examined in the next chapter.

Chapter 4: Competition and Clients' Decisions in the Pension Funds Market

4.1. INTRODUCTION

Several studies in the U.S. mutual funds literature have focused on the relationship between fund flows and performance. They have found that clients asymmetrically respond to past performance. I study this relationship as well as which funds in the Chilean pension fund market include advertising among their strategies to attract clients. The special setting provided by the laws regulating Chilean pension funds, in which peer relative performance comes out as the market benchmark, offers an interesting opportunity to comprehend how customers react to performance and what it is that pension funds publicize in their marketing policies.

In a previous study, I describe the existence of similarities in pension fund returns and infer that the similarities can be attributed to the tendency of managers to mimic each other's investment strategies. It is in this context that, in the present study, I examine how the clients choose among funds and how the pension funds compete to attract customers. In particular, I examine whether past performance or ranking on performance influences the investors' decisions, and whether the fee scheme and standard deviation of returns have an impact on fund flows. The second aim of this chapter is to study how pension funds compete to attract their clients. I examine whether advertising is commonly used to divulge information about significant events such as past performance and reductions in fees. To also evaluate how long a marketing campaign lasts, the share of marketing expenses is computed across funds on a rolling basis of 1 month, 3 months, 6 months, and 12 months and is run with the independent variables of *performance, ranking,* and *fees.*

Several studies on the flow–performance relationship have shown the importance of past performance on investors' decisions (Ippolito (1992), Gruber (1996), Chevalier and Ellison (1997), Goetzmann and Peles (1997), Sirri and Tufano (1998), Zheng (1999), Del Guercio and Tkac (2002) and Huang *et al.* (2003)). Some of them find non-linearity in the relationship, and some find that fund flows do not reflect flight from poor performers. In contrast, Del Guercio and Tkac (2002) show that U.S. pension funds exhibit not only linearity in performance but also that customers run away from poorly-performing funds and that there is only a weak incentive for managers to alter the portfolio risk due to the explicit punishment for deviating from plans.

I measure net fund flows as monthly percentage variation in asset values adjusted by appreciation and mergers, and divide this flow definition into parts: net percentage change in account size (value flow) and the number of clients (quantity flow). In addition, I use percentage change in the number of clients (client flow).[41] The performance is assessed as both raw return and excess return over the benchmark, the weighted average return across funds, for different rolling periods: 1 month, 3 months, 6 months, and 12 months.

I find evidence of a positive and non-linear relationship between flows and past-12-months performance. This result is mainly due to changes in the larger accounts (*value flow*), which correspond to elderly or wealthier clients. I also find that the number of clients in each fund remains relatively steady despite some funds being classified as losers in the ranking—that is, clients are less performance-sensitive to poor performers. In other words, only the best-performing fund is able to get positive net flows driven by large saving accounts. Runner-up funds do not experience significant changes in the

[41] Del Guercio and Tkac (2002) use change and net percentage flows in asset values not adjusted by mergers. As a robustness check, they use percentage change in the number of pension clients. My definition of client flow is adjusted by mergers.

level of consumers. I also document a negative relationship between net flows and both types of fees. Similar to the findings of Sirri and Tufano (1998) and Barber *et al.* (2002), I find that investors are fee-sensitive and make their decisions on the basis of management fees.

I find that the biggest marketing efforts are mainly carried out by the winner fund in order to promote its past performance. Funds that rank lower tend to spend less on their marketing strategy. I also find that the best performer increases its share of advertising expenses in a period between 1 month and 3 months. This finding seems consistent with the notion of the lack of stability in maintaining first place in the ranking of funds. Additionally, in the period under study, I observe a systematic drop in industry variable fees, something that is also stressed in the advertising campaigns. My results support the idea that clients rely on the information about fees and performance provided by media advertising and by salespersons' visits.[42] Marketing campaigns are short-lived. The winner fund increases its advertising during the next three periods after achieving first place in the ranking.

In sum, the results show a non-linear relationship between fund flows and performance. Because of frequent fluctuation in which fund is the winner fund, clients neither flee poorly-performing funds nor do they flock to the best performer. Lower fees and past-12-month performance explain the percentage change in fund flows but not the flow of clients. The evidence also suggests that PFA marketing strategies exclusively emphasize the top-performing fund during the three months after the fund reached first place. I find that volatility is not significant. I think the MGR encourages a lack of differentiation among fund returns, and the penalty for falling below it spurs managers to not alter their portfolio risk, even if they are behind in ranking. The explicit punishment

[42] Sirri and Tufano (1998) perfectly describe a similar situation in U.S. mutual funds arguing that households are not trained in financial analysis and their purchasing decision is related to search costs.

outweighs the implicit reward to attract flows by altering the portfolio risk. Incentive contracts may be seen as financial future-like rather than call option-like, as exhibited in the U.S. mutual fund market.

4.2. DESCRIPTION OF MARKET SHARE, FEE SCHEMES, REVENUES, EXPENSES AND ASSETS

4.2.1. Market Share in the Pension Funds Industry (June 1997–December 2001)

In the sample period, the number of PFAs went from thirteen (in 1997) to seven (in 2001) as a result of a series of mergers. Mergers have been the most effective mechanism used by funds to increase market share. The absorbed institutions were not capable of achieving the break-even point in the number of clients. Table 4.1 illustrates the evolution of the market share of survivor and defunct funds through time, measured by the number of clients (Panel A) and by asset values (Panel B). By 2001, the largest fund (PFA Provida) has 40 percent of all clients and 31 percent of assets. With 6.9 percent of the clients but 17.5 percent of the assets, PFA Cuprum has the greatest account value per client. Another crucial feature in the sample period was the drop in mean value of monthly variable fees across funds from 3.0 percent to 2.5 percent. Unlike the pension fund market, Chilean mutual funds epitomize a steady growth in the number of funds and dissimilarity in performance. As of December 1999, there existed 14 mutual funds with 115 funds, and in 2001, this industry was composed of 17 mutual funds and 177 funds. Their asset values, equivalent to 10 percent of PFAs' asset values, grew between those years from $2,151 million to $3,313 million. Also, regulation of mutual funds is less restrictive than that of pension funds. Investment constraints are fundamentally focused on avoiding concentration by security issuers[43]. Neither the government nor mutual funds are obligated to guarantee any minimum return on funds. Each mutual fund may charge any fee by management on the basis of asset values. PFAs, on the other hand, cannot charge fees on asset values. Within each category, mutual funds have exhibited a wide range of management fees and returns. In fact, Maturana and Walker (1999) find that stock funds present similar returns to passive strategies, but the differences in annual returns among funds are as large as 10 percent.

4.2.2. Fee Schemes and Revenues

Pension fund fee schemes are composed of a fixed fee and a variable fee. PFAs may charge any fee plan, but that fee plan must be uniform for all their clients. Furthermore, no management fee is allowed on asset values. PFAs are prohibited from creating new funds to increase the *degree of product differentiation,* unlike Chilean mutual funds[44].

Each dependent worker is obligated to hold a personal savings account in only one PFA and is not allowed to redistribute the resources among several funds. Each month, workers must contribute 10 percent of their taxable income (salary) to their individual accounts and pay both management and life insurance fees[45]. Although the law allows each PFA to freely decide its fee plan, pension funds may only charge two types of monthly commissions, a fixed fee and a variable fee. The fixed fee is a monthly flat amount of money charged by management. The variable fee is entirely calculated as

[43] Unlike mutual fund regulation, PFA legislation considers liquidity and concentration factors to estimate the investment constraints. Olivares (2003) describes the PFA constraints.

[44] Massa (2003) uses the term *degree of product differentiation* to refer to competitive strategies employed by mutual fund families. Khorana and Servaes (2003) find that when a fund family outperforms competitors, starting a new fund is an *innovation* factor in this competition.

[45] The PFA legislation establishes a maximum taxable salary ($950,000 as of December of 2001) to make contributions to a savings account—that is, the maximum revenue per client that a PFA may realize is the variable fee times $950,000. However, over this amount, workers may freely decide to make additional payments without paying any additional fee.

a percentage of the monthly taxable incomes of workers. In 2001, the average monthly fixed and variable fees were $581 and 2.5 percent, respectively. For instance, if the worker's taxable monthly salary were $800,000, then the PFA monthly revenues would be $20,581. Additionally, PFAs are not permitted to apply distinct commissions to clients on the basis of either taxable salaries or savings account balances. In effect, the law precludes the possibility of discrimination in fees among consumers and mandates that both types of fees must uniformly be charged to each client. No fee is allowed to be charged on the assets value of savings accounts. This means that if a worker is fired or otherwise interrupts his stream of monthly wages, then the PFA would not get any commission.

Fixed and variable fees represent 91 percent of PFAs' total revenues[46]. PFAs' variable fees represent 80 percent of total revenues. Table 4.2 lists monthly values of some revenues, expenses, and asset values. Table 4.2–Panel A describes monthly average values of revenues and fee plans for each year.[47]. The variable fee diminishes from 3.0 percent to 2.5 percent, and the fixed fee increases from $216 to $581. The final effect of these variations in fees is illustrated by total income per client, which has ranged from $4,029 to $4,296. This variation is equivalent to a decrease of 6.7 percent in real terms; however, the earnings realized by PFAs per client reflected in net operating income skyrocketed 324 percent, from $355 to $1,508.

[46] The remaining 9 percent comes from capital gains of the Mandatory Reserve account. This account operates as a margin account and is equivalent to 1 percent of managed funds; it is invested in the same portfolio as the fund's portfolio. This account is deposited in the Central Bank of Chile to guarantee compliance with the minimum return of funds. See Olivares (2003) for a more extensive analysis of the minimum return.

[47] At the bottom of Table 3–Panel C, I present the values of the exchange rate ($ per US$) and inflation rate (percent) if the reader wants to translate Chilean pesos to US$ for both nominal and real values.

4.2.3. Expenses and Assets

With respect to expenses, salespersons' commissions, administration, personnel, and marketing (advertising) are the most important in size. The most remarkable characteristic of Table 4.2–Panel B is the ratio expenses-to-revenues, which persistently shrinks through the years from 0.82 to 0.61. I suspect that the primary reason for this systematic fall rests on the abrupt drop in ratio salespersons-expenses-to-total-expenses, which varies from 0.35 to 0.14 due to a regulatory change that limited the number of clients' transfers from six to two among funds within a year; as a consequence, PFAs reduced their sales forces. Despite the considerable reduction in variable fees, there was a substantial increase in the net operating income per client, as shown in Table 4.2–Panel A, which might be due entirely to the lessening in expenditures, i.e., in salespeople's commissions. The marginal contribution per client dramatically increased by \$1,153 (from \$355 to \$1,508), while salespersons' expenses per client decreased by \$940 (from \$1,305 to \$365) due to the significant reduction of the number of salespersons in the pension funds system. Table 4.2–Panel C shows that the total assets value managed by pension funds has systematically grown (in pesos), despite severe falls in the stock market because of the Asian and Russian crises.[48]. As of 2001, the total value of the funds reached \$22,100 billion (US\$35.0 billion), equivalent to 50 percent of the Chilean GDP.[49]. The number of clients steadily increases every period. On average, the monthly growth rate of new clients going into the system is around 0.24 percent, which is slightly higher than the national population growth rate. As mentioned, the most significant event in this market was the variation in salesperson expenses. During the sample period, the

[48] In 1997-98, stock holdings accounted for nearly to 30 percent of portfolio value. Stock market returns during the Asian and Russian crises accounted for -30 percent and -28 percent respectively.

[49] The exchange rate between the Chilean peso and the U.S. dollar increased from \$417 to \$670 in the period 1997:06–2001:12.

number of salespersons decreased drastically, by 86 percent. As a proportion of total workers of PFAs, the level of salespersons shrank from 79 percent to 43 percent during the sample period.

To get a more informative overview of the features of distinct PFAs, I calculate ratios of revenues, expenses, and net operating income relative to asset values and I classify PFAs into four different groups: industry value (computed on industry values), merged funds (those acquired by other funds), survivors, and leaders (three largest funds).[50] Table 4.3 displays these ratios that are determined as of December of each year. The fee scheme across groups does not exhibit important differences at the end of each year. However, in 1997, merged funds disbursed more in marketing expenses and realized operating losses, unlike the leader funds, which exhibited the lowest ratio in expenses and the largest operating profits. Leader funds always made an operating benefit over fund assets near 0.5 percent. Survivor funds spent less money on expenses than leader funds, but their fees were very similar to those of the leaders.

4.3. DATA AND METHODOLOGY

4.3.1. Data

The data used in this study is directly obtained from the Chilean Superintendence of Pension Funds Administrators and covers the period June 1997 to December 2001. It includes monthly information per pension fund on interim income statement reports, stock prices, fund asset values, fund quota values, and general statistics on the numbers of clients, salespersons, and workers. In the sample period, there are two types of funds managed by each PFA; however, fund type II wasn't in operation until 2000, so this study focuses only on fund type I. The database is free of survivorship bias and is

[50] Each PFA has its own financial statement completely unrelated to its pension fund. Pension funds have no liabilities, only assets and equities. However, I use the terms PFA and pension funds interchangeably.

presented as panel data.[51] The number of pension funds decreases through the sample period from thirteen to seven. The fund return is determined using the quota values between two periods beginning with May 1997. Quota value refers to the fund assets value divided by outstanding shares.[52] The monthly contributions of clients are expressed in number of quotas. As most of the variables, expressed in domestic currency, come from income statements, I compute the monthly variation of incomes and expenses. The cumulated return is determined by 1-month, 2-month, 3-month, 6-month, 9-month, and 12-month periods, and so is the standard deviation of such returns.

4.3.2. Hypotheses

The two questions I want to examine are (i) how clients choose among funds and (ii) what pension funds advertise to compete and to attract customers. To address the first question, I investigate the relationship between fund flows and performance to examine whether past performance matters to clients. Several studies on U.S. mutual funds have documented that investors asymmetrically respond to past performance. However, the case of Chilean pension funds may not necessarily follow that pattern. In addition, unlike mutual fund investors, clients have neither investment agents nor financial advisors to advise them on the distinct opportunities offered by funds. Their inability to understand the meaning of risk–return may be another reason to think that performance might not matter. I investigate whether ranking on past performance affects fund flows. Ranking is another way to refer to the importance of performance of a fund in relation to others. Through ranking variables, I study whether clients tend to move toward better performing funds, that is, if the place in the ranking is informative to clients. I also examine whether clients focus on fixed and variable fees as a factor in choosing among funds. If funds

[51] Zheng (1999) argues that mergers do not provoke survivorship bias because her tests include the defunct funds before they disappear. Likewise, I do not exclude any fund in our sample even if it has merged.
[52] These shares are not traded in markets.

present statistical differences in returns, then lower fee schemes tend to attract more fund flows.

The second question is how PFAs try to lure fund flows. To answer this question, I analyze the variables (performance and fees) that are stressed in PFAs' marketing strategies by examining marketing and salesperson expenses. I specifically calculate as dependent variables the changes and the weight of both expenses. Changes refer to variation in expenses between two periods, and weight means the share of expenses disbursed by PFA(i) over the total expenses incurred by the whole set of pension funds. The same normalization is realized for the variable: number of salespersons for a fund (i) over the total number of salespersons. In fact, what I want to evaluate is whether a fund's advertising policy changes when it (i) performs better or (ii) lowers its fee schemes or (iii) simply advertises to be competitive in the market—that is, whether funds with superior performance or high ranking or with lower fees tend to increase their advertising expenses to attract clients.[53] In addition, I study how long the marketing campaign is carried out by funds.

4.3.3. Methodology

4.3.3.1. Flow Measures

In order to answer the first question, I define fund flows as the monthly percentage change in asset values adjusted by appreciation and mergers. This approach is more suitable than the simple change in flows because larger PFAs tend to receive larger funds irrespective of their performance.[54] To determine the net percentage change in asset values exclusively caused by movement of clients' cash flows, I subtract not only

[53] For instance, Sirri and Tufano (1998) find media attention considers bad and good performers equally.

[54] Market share in asset values, from Table 1, has remained constant across funds. Only mergers have realized great inflows to acquiring funds.

the appreciation of fund assets given by a fund's past return over the prior month corresponding to capital gains and dividends, but also the increase in total assets derived from mergers. When a fund is merged into another fund, automatically its assets are augmented by the total asset value of the other fund. Adjustment by mergers is of tremendous importance in my flow definition because around half of the funds disappeared by this process. Table 4.1 illustrates the relevance and impact of this point. For instance, PFA Provida increased its market share by 4.3 percent, in terms of asset values, after acquiring PFA Union, which had accounted for 4.5 percent of the market share. Almost 96 percent of PFA Union's client resources remained in PFA Provida. When an acquiring fund holds a great proportion of a defunct fund's money, it is called "follow the money" approach and is described by Elton, Gruber, and Blake (1996), Gruber (1996), and Zheng (1999) for the mutual funds industry. These authors (unlike me) assume the existence of this pattern to control for survivorship bias.[55] Numerous studies employ the measure of flow as asset values minus appreciation scaled by past period asset values.[56] However, only two incorporate the variable *mergers:* (Zheng (1999) and Huang, Wei, and Yan (2003).

Fund flows of each fund are measured by *Flow_Pesos*, given by Model (4.1), which corresponds to percentage variation in asset values, adjusted by investment return and mergers. $Asset_{i,t}$ is the asset value of the fund (*i*) at the end of the month (*t*) (in local currency), $Return_{i,t}$ is the return of fund (*i*) during the month (*t*), and $Merger_{i,t}$ accounts for

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[55] After studying only two cases, Gruber (1996) finds 90 percent of funds remain in the acquiring fund. In this paper, the evidence is almost 95 percent.

[56] Gallaher, Kaniel, and Starks (2004), Huang, Wei, and Yan (2003), Barber, Odean, and Zheng (2002), Shu, Yeh, and Yamada (2002), Jain and Wu (2000), Sawicki (2001), Sirri and Tufano (1998), Chevalier and Ellison (1997), Gruber (1996), Ippolito (1992). Other papers, such as Del Guercio and Tkac (2002) and Zheng (1999), use change in dollar flow despite checking robustness by using percentage change in flow.

increases in $Asset_{i,t}$ due to mergers. With regard to specification data, changes in flows occur at the end of each month.

$$(4.1)\ \ Flow\_Pesos_{i,t} = \frac{Asset_{i,t} - Asset_{i,t-1} * (1 + Return_{i,t}) - Mergers_{i,t}}{Asset_{i,t-1}}$$

Similarly, the percent change in the value of funds between (t_1–t_0) may be written as:

$$(4.2)\ \ Flow\_Pesos_{i,t1} = \frac{\left(\dfrac{Asset_{i,t1} - Merger_{i,t1}}{Clients_{i,t1}}\right) * Clients_{i,t1} - \left(\dfrac{Asset_{i,t0} * (1 + Return_{i,t1})}{Clients_{i,t0}}\right) * Clients_{i,t0}}{Asset_{i,t0}}$$

The term $Clients_{i,t}$ refers to the number of clients in the fund (i) at the end of month (t). Model (4.2) may be divided into two parts, which I will call (4.2a) *Value_Flow* (*VF*) and (4.2b) *Quantity_Flow* (*QF*) such that *Flow_Pesos* is equal to *Value_Flow* plus *Quantity_Flow*.[57]

(4.2a)

$$Value\_Flow_{i,t1} = Clients_{i,t0} * \left[\left(\frac{Asset_{i,t1} - Mergers_{i,t1}}{Clients_{i,t1}}\right) - \left(\frac{Asset_{i,t0} * (1 + Return_{i,t1})}{Clients_{i,t0}}\right)\right] * \frac{1}{Asset_{i,t0}}$$

$$(4.2b)\ Quantity\_Flow_{i,t1} = \frac{\left(Asset_{i,t1} - Merger_{i,t1}\right)}{Clients_{i,t1}} * \left(Clients_{i,t1} - Clients_{i,t0}\right) * \frac{1}{Asset_{i,t0}}$$

The percentage variation in *Flow_Pesos* is driven by *VF*, the percentage change in the asset value per client (variation in value), and *QF*, the percentage change in the number of the clients (variation in quantity).[58] This separation of flows allows us to capture the effect in changes in funds driven by investors with larger accounts (Value), i.e., older or wealthier clients, or by the mass of clients (Quantity).

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[57] To obtain (4.2a) and (4.2b) from Model (4.2), I add and subtract the term $\pm\left[(Asset_{i,t1} - Merger_{i,t1})/Clients_{i,t1}\right] * Clients_{i,t0}$ and later I reorder the factors.

[58] To my knowledge, no one has documented this separation to study flows. Del Guercio and Tkac (2000), in spite of holding the number of pension clients, do not use this analysis.

Finally, I measure the percentage variation in the number of clients in a PFA, defined by *Flow_Clients* with Model (4.3). In this model, $Clients.Merger_{i,t1}$ refers to the quantity of clients added to fund (i) from fund (j) with ($i \neq j$) at time (t) due to mergers.

$$(4.3)\quad Flow\_Clients_{i,t} = \frac{Clients_{i,t} - Clients_{i,t-1} - Clients.Merger_{i,t}}{Clients_{i,t-1}}$$

In Table 4.4, I illustrate the analysis of flow definitions of the four flow definitions before and after the series of mergers to better comprehend the changes in this industry. Before any mergers (1997:06–1998:05) in Table 4.4–Panel A, four of six defunct PFAs mainly exhibited negative *Flow_Pesos* explained by reduction in *Quantity_Flow*, i.e., by drops in the number of clients, even though the entire industry's monthly flow grew by 0.37 percent. Not only did these funds consistently lose clients, but they also disbursed more in operating expenses. They could never reach their break-even point. In Table 4.4–Panel B, we see that after four mergers, all of the fund survivors experienced positive flows, and the industry's *Flow_Pesos* monthly growth rate reached 0.29 percent, driven also by the number of clients (*QF*). Table 4.4–Panel C lists the seven fund survivors, after six mergers. The industry steadily grew to 0.25 percent, influenced by the quantity of clients. Results obtained from *Quantity_Flow* are equivalent to those from *Flow_Clients*.

4.3.3.2. Marketing Variables

Clients receive information about performance through two mechanisms. First, PFAs are obligated to issue quarterly savings account statements informing their clients about the monthly inflows, ending balances, management fees, and the annual achieved return. Second, the Superintendence of Pension Funds Administrators (SPFA) holds a monthly press conference to disclose monthly and yearly returns achieved by the system as a way to diminish the cost of informing clients about the funds' performance and to encourage competition within the industry[59]. In fact, as a way to compete, PFAs frequently advertise their performance in the past 1 to 12 months. As a mechanism to make this information clearer to clients, PFAs commonly realize ranking based on these performances. To address the question of how PFAs compete to draw clients, I examine whether pension funds advertise past performance and fee schemes in their marketing strategies. As part of these marketing strategies, funds utilize advertising, direct mailing, and salespersons.

Information on marketing expenses is obtained from monthly income statement accounts. Marketing is measured by considering both the variation of monthly advertising expenses and the proportion of advertising expenses of a PFA over the industry's. Salespersons' activity is mainly assessed by the share of the number of salespersons of fund (i) over the total salespersons in the industry. I disregard the change in salespersons' commissions because the number of vendors systematically shrank and so did commissions, as explained previously.

Two different regression models are run using *changes* in marketing expenditures and the *weight* of marketing expenses as dependent variables. The weight of marketing expenses is defined as the advertising expenses of fund (*i*) over the total advertising expenses of the industry for period (*T*). For instance, in 1997:06, PFA Cuprum spent M$944 on advertising, while the whole industry disbursed M$5,080; thus, the *weight_marketing* of PFA Cuprum is 18 percent.[60]. This last variable allows capturing the effect of whether a PFA's increase in advertising is proportionately larger than that of the industry since *all* pension funds increase their advertising in several of the periods.

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[59] Aside from past performance, the SPFA informs on total assets evolution, number of clients, total revenues, earnings, and returns realized by pension funds administrators.

[60] Market share of PFA advertising expenses (i) is $\alpha_i = [PFA\ Advertis\_Expenses_{(i)} / \sum PFAs\ Advertis\_Expenses]$ where $\sum \alpha_i = 1$

The three independent variables are performance, fixed fees, and variable fees, and the two control variables are fund size and standard deviation of past performance.

Several papers on mutual funds examine the effect of marketing expenses. Sirri and Tufano (1998) compute marketing expenditures and the weight of media citation of major periodicals (a fund's share of media citation over the total industry's media citation) as measures of search costs, assuming that high fees can be considered a good proxy for these expenses; however, they are not sure that high fee funds correlate with high marketing funds. Jain and Wu (2000) test whether advertising is used to attract more money to advertised funds; they find that flows are larger to advertised funds. Barber, Odean, and Zheng (2002) argue that investors learn to avoid load funds; they also find a negative relationship between flows and load fees. Mamaysky and Spiegel (2001) design a model to explain the existence of fund families that emphasize investors who prefer dynamic trading strategies and do not stay in the market all the time. Khorana and Servaes (2003), in analyzing fund family strategies, show that fund families gain market share with lower fees and with higher performance. Massa (2003) claims that even when a fund family underperforms, it may remain competitive by shrinking fees or offering more funds within the family to attract heterogeneous clients. Gallaher, Kaniel, and Starks (2004) focus on the determinants of flows to fund families and find that advertising has no linear impact in flows and that there is no relation between advertising expenses and fund flow volatility.

4.3.3.3. Specification of Regression Models

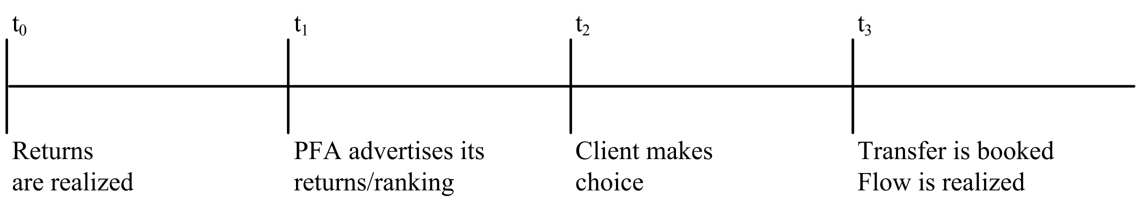
The dependent variables are *Flow_Pesos*, divided into *Value_Flow,* and *Quantity_Flow* and *Flow_Clients*[61]. I measure performance in three ways: as excess

[61] *Flow_Pesos* and *Flow_Clients* are the main dependent variables used to study the relationship between flows and performance. The use of the latter variable constitutes my unique contribution to the knowledge of this topic.

returns over the benchmark (premium), as excess returns over the average return of industry, and as raw fund returns. As the benchmark, I use the weighted average return across funds, which is used by the SPFA to determine the accomplishment of the minimum guaranteed return (MGR). I do not preclude, *a priori*, any length of period to measure performance. These performance definitions are measured on the basis of rolling months of 1, 6, and 12 months (*T=1,6,12*) to determine what performance period is the most important to clients when making their decision. From premium in returns, I proceed to rank PFAs from the highest (with value=1) to the lowest (with value=13) past performance and classify PFAs into three categories: top place (winner fund, with value=1), middle place (funds with values=2, 3, 4, 5), and bottom place (funds with values=6 through 13). As the number of PFAs decreases (through mergers), the bottom place gathers values numbers 6 through the number of funds existing. In addition, I define a set of dummy variables to precisely represent the final position in the ranking of each PFA. For instance, Ranking_1^{st} is equal to 1 if fund is the winner and 0 otherwise. Ranking_2^{nd}_3^{rd} is equal to 1 if the fund achieved either second or third place in the ranking and 0 otherwise.

Because fund flows have a delayed response to the explanatory variables, I consider that there is a 3-month lag between the explanatory variables and the time the fund flow occurs, as represented in Diagram 1:

Diagram 1. Timeline of the Decision-Making Process



The timing of the pension fund system's information disclosure starts when the SPFA reveals the monthly- and yearly-earned performance of each PFA at the end of each month (t_0).[62]. This official information is heavily used by PFAs to advertise past performance in the period. The more aggressive marketing campaigns advertise through both media and salespersons.[63]. Media coverage includes ads in newspapers and TV. Similar to Sirri and Tufano's (1998) comment on mutual fund consumers, pension fund clients are incessantly bombarded by vendor solicitations. Salespeople engage in cutthroat competition to get appointments to visit potential new customers, because an important part of their compensation is based on the number of clients that they capture. Unlike mutual funds, pension funds directly commercialize their product through vendors and branches. No external institution is allowed to distribute the pension funds service. During the period of great exposure to PFAs' marketing activity (t_1), clients make their choice. Their decision to transfer their funds from PFA (i) to PFA (j) takes effect when they sign the transfer forms provided by a salesperson or at any branch office (t_2). Each PFA processes the transfer papers by checking appropriate signatures and clients' identification data. After transfer forms have been cleared, PFA (i) proceeds to pass on funds to PFA (j). This final step is booked by both PFAs in their accounting system, and their magnetic tapes are forwarded to the SPFA, which confirms the transfer of funds and discloses it at (t_3).

Diagram 1 is read as follows: returns are endogenously realized at the end of month (*t*), and PFAs advertise this information throughout the following month (*t+1*).[64] During that period, clients are exposed to advertising, and then they select a fund in the

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62 Monthly and annual returns are computed on a calendar-month basis.

63 The Pension Fund Act exclusively allows PFAs to advertise and promote information to clients relative to investments, performance, fee schemes, type of funds, number of branches and market share.

64 As financial reports are referred to at the end of each month, I assume that advertising expenses may happen during the month.

following month ($t+2$) by signing the transfer document, which is processed in the next period ($t+3$) by PFAs. In that last period, inflow and outflow are recognized in *Flow_Pesos* and *Flow_Clients*. As a change in fee is a non-endogenous decision, PFAs may decide when to modify their fee schemes and immediately advertise this change. Flows would be booked at (t_2).

Returning to the first of my two questions (how clients choose among funds and what pension funds advertise in order to compete), I follow Sirri and Tufano's (1998) approach (exhibited in their Table 2) and define the following specification that relates excess returns, fees, and total risk to regression Models (4.4) and (4.5), which consider as dependent variables *Flow_Pesos* and *Flow_Clients*.[65]

$$\begin{aligned} Flow\_Pesos_{i,t} = \alpha + \beta_1 FixFees_{i,t-1} + \beta_2 VarFees_{i,t-1} + \beta_3 Premium_{i,t-k}Tmonth + \\ \beta_4 LOG(Asset)_{i,t-1} + \beta_5 Standard.Deviation_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4.4}$$

$$\begin{aligned} Flow\_Clients_{i,t} = \alpha + \beta_1 FixFees_{i,t-1} + \beta_2 VarFees_{i,t-1} + \beta_3 Premium_{i,t-k}Tmonth + \\ \beta_4 LOG(Asset)_{i,t-1} + \beta_5 Standard.Deviation_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4.5}$$

Variables $FixFee_{i,t-1}$ and $VarFee_{i,t-1}$ refer to the fixed and variable fees, respectively.[66] Performance, $Premium_{i,t-k}\_Tmonth$, is assessed as (i) excess return over the benchmark, (ii) excess return over the average return, and (iii) raw returns for the rolling periods of 1, 6, and 12 months ($T=1,6,12$) and with up to three lagged months ($k=1,2,3$). This model is run cross-sectionally for each individual holding period to determine what past month effectively drives movements in flows. In addition, the model employs the control variables $LOG(Asset)_{i,t-1}$, which refer to the natural logarithm of asset values of fund (i) to account for the effect of fund size (i.e., the fact that \$1 of fund flow has a more significant influence on smaller funds) and $Standard.Deviation_{i,t}$, the standard deviation

[65] The definition of *Flow_Clients* has not been explored in the context of U.S. mutual funds. Del Guercio and Tkac (2002), to check robustness in results of their *Flow* variable (in \$ and in percent), use growth in the number of clients for the U.S. pension fund segment.

[66] The data delivers disaggregated information of fixed and variable fees per PFA. Each PFA must charge the same fee schemes to its clients.

of 3-month returns as measures of a fund's total risk.[67] Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), and Huang, Wei, and Yan (2003) have extensively demonstrated the effect of performance volatility on fund flows. If funds reward managers based on asset level, and if clients react to past performance, then managers have an implicit incentive to lure more clients by altering portfolio risk, especially if they have underperformed benchmarks.

Among the most relevant works on mutual funds that have employed Model (4.4) are:

- Sirri and Tufano (1998), who use a breakdown of performance ranking in quintiles and control variables $LOG(Asset)_{i,t-1}$, monthly standard deviation, total fees, and fund category.
- Huang, Wei, and Yan (2003), who regress performance and control by $LOG(Asset)_{i,t-1}$, expenses ratio, and fund age.
- Del Guercio and Tkac (2002), who include excess returns, Jensen's alpha, and tracking error.
- Shu, Yeh, and Yamada (2002), who regress performance, fee ratios, standard deviation, account size, and turnover ratio.

However, with regard to Model (4.5), Del Guercio and Tkac (2002) reduce the importance of the variable growth of the number of clients to robustness.

As in Sirri and Tufano (1998) (in their Table 6), I examine what PFAs advertise in their strategies and use the following model:

$$\begin{aligned}(4.6)\quad & Weight\_Marketing\_Tmonth_{i,t} = \alpha + \beta_1 Dummy.Ranking\_12m_{i,t-2} + \beta_2 VarFees_{i,t} + \\ & \beta_3 LOG(Asset)_{i,t-1} + \beta_4 Change.Tot.Expenses_{i,t} + \beta_5 Standard.Deviation_{i,t} + \varepsilon_{i,t}\end{aligned}$$

[67] *Log(Asset)* helps control when fund flows may be positively correlated to fund size. In fact, as shown in Table 4.1, larger funds tend to attract more funds because their market share increases slightly.

The dependent variable, weight of marketing expenses of each fund (*i*) for different rolling cumulative periods (T =1,3,6,12 months), is regressed against the dummy variables of position in the ranking on past-12-months performance (1st through 13th) and variable fees and against control variables fund size ($LOG(Asset)_{i,t-1}$), change in total expenses, and standard deviation of past-3-months return. I consider four different periods to measure the cumulative effect of marketing expenses in order to know whether funds advertise their attributes for short or long periods. I run one regression for each period (T) with different dummy variables on ranking. With this model I may investigate how long a PFA advertises its performance ranking and whether a PFA changes its advertising expenditure depending on its position in the performance ranking. Other types of specifications exhibited in the literature are empirical works such as Sirri and Tufano (1998), who use as a dependent variable the weight of media citation of major periodicals against performance quintiles, fees, monthly standard deviation, $LOG(Asset)_{i,t-1}$ and fund complex assets. Jain and Wu (2000) regress flows against a dummy variable for advertised funds and control by size and past performance and flows.

I estimate both types of regression models using the methodology proposed by Fama and Macbeth (1973), broadly used in the literature of mutual funds (by Gallaher, Kaniel, and Starks (2004), Huang, Wei, and Yan (2003), Shu, Yeh, and Yamada (2002), Sawicki (2001), and Sirri and Tufano (1998)). Specifically, I carry out 43 cross-sectional regressions on fund flows across PFAs for each month and inform the means and t-statistics from the time series of coefficients.[68] The Fama-Macbeth procedure provides more suitable standard errors than a pooled OLS model, which tends to understate standard errors and hence overestimate t-values because monthly observations may be correlated with previous months. However, given the small number of PFAs existing in

[68] Shu *et al*. (2002) study a sample of 37 open-end equity mutual funds in Taiwan between 1996:11 and 1999:10 and run 36 cross-sectional regressions. Sawicki (2001) examines 55 Australian funds for 15 years.

the market (only seven since 2001:02), the Fama-Macbeth approach shows a significant statistical problem with the degrees of freedom. Therefore, I use fewer than six explanatory variables in the regression models for a better econometric analysis. Nevertheless, and using the same set of variables, I alternatively estimate a fixed-effects model to check robustness of the findings. The estimation disregards cross-sectional variation in the data that is common to funds over time as mentioned by Ippolito (1992).[69] Besides, a fixed-effect model is more suitable, considering that our data contains all pension funds (*i-th*), allows controlling for any individual heterogeneity, and reduces the aggregation bias.[70] In this type of model, intercepts are different for each *i-th*, but slopes are constrained to be the same across units. Each regression model is tested under a fixed-effect model by using the Hausman specification test, which suggests that if there is a correlation between the unit-specific residual error (u_i) and the set of explanatory variables (X_{it}), then OLS with fixed effect emerges as a consistent model. In the tables, I report results of coefficient values and their t-test values obtained by the Fama and Macbeth (1973) approach and by the fixed-effect model. [71]

4.4. HOW DO CLIENTS CHOOSE AMONG PENSION FUNDS?

In this section, I consider how clients choose among funds by studying how fund flows move across funds and whether past performance and fee schemes affect movements of flows.

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[69] Ippolito (1992) runs a pooled regression model that exhibits the aforementioned problems. To correct these issues, he utilizes a fixed-effect model.

[70] The general estimating model is $y_{it} = \alpha + X_{it}\beta + u_i + \varepsilon_{it}$ and the fixed-effect model is represented as $(y_{it} - \overline{y}_i) = (x_{it} - \overline{x}_i)\beta + (\varepsilon_{it} - \overline{\varepsilon}_i)$. Intercept is not reported as output since it is equivalent to $(\alpha + u_i)$. Fixed-effect is Least Squared Dummy Variables (LSDV) model, where each unit (*i-th*) is a dummy variable. *Ui* refers to the extent to which α of the cross-sectional PFA (*i-th*) differs from the overall intercept.

[71] I also estimate t-statistics using Newey and West's (1987) autocorrelation and heteroskedasticity consistent standard errors, and the results are still consistent with those presented.

4.4.1. Does Past Performance Matter?

I examine the relationship between flow and past performance through the dependent variables *Flow_Pesos* and *Flow_Client*. To find out whether past performance matters in a scenario of similar returns, I run Models (4.4) and (4.5) with past performance of 1-month, 6-month, and 12-month periods (*T=1, 6, 12*), lagged 3 months.[72] Each regression is individually run to determine to what extent flows react to different rolling periods (*T*), and the results are listed in Table 4.5–Panels A1 (*Flow_Pesos*) and A2 (*Flow_Client*) with the Fama-Macbeth method and Table 4.5–Panels B1 and B2 with the fixed-effects model, respectively. Each month-period is presented in 3 different models: A (*T=1 month*), B (*T=6 months*), C (*T=12 months*) under Fama-Macbeth methodology and with a fixed-effect model. I find that flows do not respond to 1-month and 6-month *premium* with 3-month lag periods, but are more sensitive to past-12-month *premium* with 3-month lags[73]. Table 4.5–Panels A1 and A2 show that fund flows are sensitive exclusively to 12 months performance, but client flows do not exhibit any significant coefficient. This means that a number of clients does not care about past performance, but a small segment of clients seeks higher performance, which may explain the significant result of 12-month performance in Model (4.4). This point deserves deeper study through the partition of *Flow_Pesos* into *Quantity_Flow* and *Value_Flow*.

In results not shown, no premium (1-, 6- and 12-months) is significant with both 1-month lag and 2-month lags (*k=1,2*). This result is consistent with Diagram 1. The importance of this finding rests on the fact that despite the returns being disclosed by the SPFA at t_0, none of the clients makes a choice at t_1. I could argue that the SPFA's press

[72] I use lagged performance up to 3 months to be consistent with Diagram 1.
[73] I also compute rolling 3-month premium and flows do not react to this period either. Results not showed.

conferences do not generate any impact on the decision-making process of clients; rather, the active advertising campaign carried out by PFAs does. Statistical evidence supports the notion that individuals delay two periods in incorporating information on new returns and in transferring their funds from PFA(i) to PFA(j) at t_2 which is reflected in PFAs' accounting at t_3.

In Model (4.4c) (using T=12 months) with the Fama Macbeth method, the coefficient of 12-month premium (*Lag3 Prem_12m*) is equal to 0.38 and significant at 5 percent. An increase of 10 basis points in this premium would imply an augmentation of 3.8 percent in flows (+0.38*10). Consistent with this evidence, in Table 4.5–Panel D with fixed effect regression, Model (4.4c) shows a 12-month premium of 0.48, significant at 1 percent. Identical findings are also achieved (but not shown) when *premium* is defined as $\text{return}_{i,t}$ minus simple average return_t.

In relation to fees, I notice from Model (4.4c) in Table 4.5–Panel A1 that fund flows go to pension funds with lower fee schemes. Variable and fixed fee regressors are negative and significant at 5 percent and 10 percent, respectively, which is also consistent with other empirical studies on U.S. mutual funds (Sirri and Tufano (1998) and Barber *et al.* (2002)). Clients prefer to pay a lower cost when there is no difference in service.[74] However, which fees have a greater impact on flows? As of December 2001, the means of variable and fixed fees are 2.5 percent and $561. With a reduction of 20 percent in the variable fee, from 2.5 percent to 2.0 percent, fund flows are forecasted to increase 2.0 percent (-4.01 * - 0.5 percent). Likewise, a drop of 20 percent in fixed fees (from $561 to $449) would increase flows 1.79 percent (-0.016 * -$112) *ceteris paribus.* The same percentage variation in the variable fee has a larger impact on fund flows than that of the fixed fee. The negative sign in the fund size variable demonstrates that changes in asset

[74] Given that returns across funds do not exhibit statistical differences and clients may not split their savings into different funds, the pension funds service is virtually a commodity.

value have a lower impact on larger funds. However, the number of clients, *Flow-Clients* in Table 4.5Panel A2, illustrates the negative signs in both types of fees, but their coefficients are not significant. A possible explanation of this result is that the whole set of clients may see the PFA service(*i*) as a substitute of PFA(j)'s in terms of performance and fee schemes. In fact, in the period under analysis, all PFAs permanently reduced their fees, which could have confused clients over the final price of management service commissions, but fund flows react to fee schemes. The standard deviation is not significant in any regressions of Models (4.4) and (4.5).

Additionally, Table 4.5–Panels B1 and B2 that compute Models (4.4) and (4.5) under the fixed-effect model present results that are in concordance with those of prior Panels. Past-12-months performance is highly significant in *Flow_Pesos* and *Flow_Clients* specified by Models (4.4c) and (4.5c) ($T=12$). In the case of *Flow_Pesos,* and comparing Fama-Macbeth to fixed effect results, 12-month performance coefficients are positive with values of 0.38 and 0.48, respectively. Fund flows negatively react to fee schemes. The significant coefficients of variable fees are very similar, -4.01 and -3.83, respectively. Fixed fees show negative and significant coefficients of -0.016 and -0.035. Similarly, in the case of *Flow_Clients*, the results under the fixed effect model (Table 4.5–Panel B2) are consistent with those of *Flow_Pesos* (Table 4.5–Panel A2). The past-12-months performance coefficient is positive and significant. Coefficient values of variable and fixed fees are -1.97 and -0.017, respectively. The standard deviation is negative, as expected, but in none of the models is it significant. In sum, findings prove to be consistent with both Fama-MacBeth and fixed effect model methodologies. Fund flows respond to performance and fees schemes; however, client flows exhibit different results. To explicate this difference in both flows, I investigate in more detail the division of *Flow_Pesos*.

In Table 4.5–Panel C, I analyze the separation of fund flows by running the regression Model (4.4) with the dependent variables *Value_Flow* (Equation (4.2a)) and *Quantity_Flow* (Equation (4.2b)) and find that in Model (4.4b) (6-month premium), performance is non-significant. In contrast, in Model (4.4c,) the 12-month premium is positive and highly significant at 1 percent in *Value_Flow*, which explains wholly the 12-month premium coefficient in *Flow_Pesos* (0.35 over 0.38).

Fees are also an important variable in describing flow movements. Percentage variation in fund flows is not driven by the number of clients (*Quantity_Flow*), but by the account size in funds (*Value_Flow*). Elderly or affluent clients with large savings accounts tend to focus more on past performance when selecting funds. I think this group of investors pays more attention to performance because small differences in returns have a larger impact on their saving account values. In contrast, I believe that the number of clients (*Quantity_Flow*) is not sensitive to performance because they hold lower savings balances and do not persistently search for differences in returns. They do not significantly appreciate that the tiny differences in performance among funds help them increase their balance. I reach the same interpretation with respect to the 12-month premium in Table 4.5–Panel D under fixed-effect. No significance is obtained in coefficients of past-6-months performance. Table 4.5–Panel E runs regressions under both Fama-MacBeth and fixed-effect for the dependent variables *Flow_Pesos* and *Flow_Clients* and uses 12-month raw return as a measure of performance; its findings are consistent with those of Table 4.5–Panels A and B. Here I note the great similarity in the regression of *Flow_Pesos* between the 12-month premium coefficients, 0.38 and 0.36, with both methodologies. The same analogy is observed when analyzing the result for the variable fee, whose significant coefficients are -4.01 and -4.17 for Fama-Macbeth and fixed-effect, respectively. For *Flow_Clients*, performance is not significant under Fama-Macbeth, but is slightly significant under fixed-effect.

Nevertheless, as illustrated in Tables 2.2, 2.3, and 2.4, if PFAs exhibit similarities in returns, one could anticipate a weak relationship between fund flows and performance. Despite the PFAs' performance being almost identical, *Value_Flow* explicates a great proportion of fund flows, showing that fund flows react to higher performance and fees. I conjecture, based on these results, that a small number of clients are more sensitive to performance than the whole group represented by *Flow_Clients* and *Quantity_Flow*, which do not respond to higher performance, as perhaps one could have expected.

In order to examine whether clients respond equally to higher performance, I study in the next section the relationship between flows and ranking through dummy variables for ranking.

4.4.2. How Sensitive Are Flows to Ranking?

To explore whether the response to performance is identical among clients and whether relative performance among funds is important, I order the 12-month premium of PFAs from the highest (value=1) to the lowest (value=13) place and classify them in three categories: top (value=1), middle (values=2, 3, 4 and 5) and bottom (value=6 through 13).[75] I also define dummy variables relative to place achieved in the 12-month performance ranking:

- *Ranking_1st*, which equals 1 if PFA (i) is in the first place and 0 otherwise;
- *Ranking_2nd_3rd*, which equals 1 if PFA (i) is in either second or third place and 0 otherwise;
- *Ranking_4th_5th*, which equals 1 if PFA (i) is in fourth or fifth place and 0 otherwise; and finally,

[75] As the number of PFAs decreases, the bottom place comprises funds ranked 6th and below.

- *Ranking 6th_lower*, which equals 1 if PFA (i) is in sixth place or below and 0 otherwise.

I denote that a fund is the winner (*Ranking_1st*) and runners-up (*Ranking_2nd_3rd*).[76] The premium definition used to calculate ranking is the excess return on the benchmark, which is computed for rolling 12-month periods and lagged 3-month periods. I do not report rankings lagged 1 month and 2 months because, similar to 12-month premium with these lags, they do not statistically explain flow variations. In the following models, I refer $Flow_{i,t}$ to the dependent variables *Flow_Pesos* and *Flow_Clients*. In Table 4.6, Panels A1 (*Flow_Pesos*) and A2 (*Flow_Clients*) present results of four regression models—(4.7) to (4.10)—under the Fama-Macbeth procedure. Models (4.8) through (4.10) regress the ranking variables pairwise to make a better comparison of the flow sensitivity on past performance between two groups.

$$Flow_{i,t} = \alpha + \beta_1 LOG(Asset)_{i,t-1} + \beta_2 Standard.Deviation_{i,t} + \beta_3 FixFees_{i,t-1} + \beta_4 VarFees_{i,t-1} + \beta_5 Dummy.Ranking1^{st}\_12month_{i,t-3} + \varepsilon_{i,t} \tag{4.7}$$

Table 4.6–Panel A1 shows a negative and statistically significant coefficient in variable fees (at 5 percent) and fixed fees (at 10 percent) in Model (4.7). The 1st place dummy coefficient in past-12 premium ranking is positive (0.006) and significant at 10 percent. This means that clients tend to follow the winner fund in the ranking. To better analyze consumers' preferences in returns, I define Model (4.8) with dummy variables of *Ranking1st* and *Ranking2nd_3rd* to refer to the fund in 1st place and funds in either 2nd or 3rd place. The outcomes illustrate that *Ranking1st* is positive (0.005) and significant (at 5 percent); however, *Ranking2nd_3rd* is positive, not significant, and lower in value. This finding supports the notion that clients do not react equally to performance. The flow sensitivity is statistically stronger in superior performers.

76 Sirri and Tufano (1998) use performance quintiles to categorize funds. In this paper, due to the number of total funds decreasing from thirteen to seven, I prefer to use smaller categories.

(4.8)
$$Flow_{i,t} = \alpha + \beta_1 LOG(Asset_{,t-1}) + \beta_2 Standard.Deviation_{i,t} + \beta_3 VarFees_{i,t-1} + \\ + \beta_4 Dummy.Ranking1^{st}\_12m_{i,t-3} + \beta_5 Dummy.Ranking.2^{nd}\_3^{rd}\_12m_{i,t-3} + \varepsilon_{i,t}$$

In Model (4.9), I change the variable *Ranking2*nd*_3*rd to *Ranking6*th*_lower*. *Ranking1*st coefficient still is positive (0.006) and significant at 5 percent, whereas *Ranking6*th*_lower* is negative in sign and non-significant. This outcome contributes to evidence that clients do not react equally to performance. Basically, the winner fund in the ranking draws fund flows of their clients, while poorly-performing funds do not change their fund flows. When using *Flow_Clients* in Table 4.6–Panel A2, no significant results are obtained. The number of clients does not seem to respond to any independent variables. As mentioned before, I hypothesize that a small group of clients drives the results of fund flows. When the fixed-effect model is used, the results of Table 4.6–Panel B1 (*Flow_Pesos*) are consistent in sign and significance with the above rankings.

(4.9)
$$Flow_{i,t} = \alpha + \beta_1 LOG(Asset_{,t-1}) + \beta_2 Standard.Deviation_{i,t} + \beta_3 VarFees_{i,t-1} + \\ + \beta_4 Dummy.Ranking.1^{st}\_12m_{i,t-3} + \beta_5 Dummy.Ranking.6^{th}\_lower\_12m_{i,t-3} + \varepsilon_{i,t}$$

(4.10)
$$Flow_{i,t} = \alpha + \beta_1 LOG(Asset_{,t-1}) + \beta_2 VarFees_{i,t-1} + \beta_3 Dummy.Ranking.1^{st}\_12m_{i,t-3} \\ + \beta_4 Dummy.Ranking.2^{nd}\_3^{rd}\_12m_{i,t-3} + \beta_5 Dummy.Ranking.4^{th}\_5^{th}\_6^{th}\_12m_{i,t-3} + \varepsilon_{i,t}$$

Slightly different from previous models, in Model (4.10) I gather three ranking variables from 1st to 6th place, *Ranking1*st*, Ranking2*nd*_3*rd and *Ranking 4*th*_5*th*_6*th. The results confirm that the top fund tends to attract more clients than those in lower positions. The coefficient in *Ranking1*st is positive (0.004), statistically significant (at 10 percent) and larger than those of *Ranking2*nd*_3*rd and *Ranking4*th*_5*th*_6*th. Performance is important to clients; however, when it is divided into categories as documented by Sawicki (2003), Shu *et al*. (2002), Sirri and Tufano (1998) and Ippolito (1992), I find that there exists an asymmetric reaction, depending on the ranking position of funds. Funds that perform better receive a stronger impact on flows than those that do worse, despite similarity in returns. Relative performance evaluation among funds matters to affluent or elderly clients when deciding on allocation. Likewise, Table 4.6–Panel B1 with Models (4.9) and (4.10) delivers the same evidence exhibited in Table 4.6–Panel A1—mainly, the best performer in the rolling 12-month period of the ranking is capable of increasing fund flows.

Now, I will examine what part of flow definition drives these results. Table 4.6–Panel B2 with the variable *Flow_Clients* exhibits no significant coefficients for ranking from 2nd place through 6th and lower. The same results are obtained for the top performer fund (1st place) in models (4.8) and (4.10). In the other two models, 1st place coefficient is consistent in sign and barely significant at 10 percent. Consistent with Table 4.6–Panel A2's results, coefficients of Models (4.8) through (4.10) of Table 4.6–Panel B2 in the variable fees are not significant. I infer that the clients' flow does not move looking for lower fees or high past performance due to the law's prohibition of the differentiation in fund services.[77] In fact, the MGR encourages the likeness in funds' performance, and PFAs cannot increase the number of new funds. As funds started steadily decreasing their fees from 1998:04, clients may have been confused in identifying which fund offered the lowest management charges. The hypothesis that clients do not perceive any significant benefits from changing from one PFA to another is supported, not only by the results of *Flow_Clients* but also by the fact that PFAs do not significantly change their market share, as illustrated in Table 4.1.

Models (4.8) and (4.9) are run using the decomposition of flows in *Value_Flow* and *Quantity_Flow,* and their outcomes are exhibited in Table 4.6–Panel C under the Fama-Macbeth procedure.[78] Model (4.8), at first glance, illustrates that *Value_Flow*

[77] Massa (2003) identifies that among fund families, different fees and new funds increase product differentiation.

[78] Results of Model (4.7) with *Value* and *Quantity* are consistent with those of Models (4.8) and (4.9) and are not shown.

drives changes in *Flow_Pesos*. The coefficient value of the *Ranking1*st variable is identical between both flows (0.005) and significant at 5 percent. In contrast, *Ranking 2*nd*_3*rd coefficients are non-significant and equal. However, *Quantity_Flow* shows that the ranking variable is not different from zero, i.e., the number of clients does not consider the ranking position material, unlike elderly or affluent clients. Consistent with the previous results, the price variable is highly important to large accounts. The variable fee is negative and significant at 5 percent. Similar evidence is inferred from Model (4.9). In both models, *Ranking1*st coefficient of *Value_Flow* explains a considerable part of the coefficient of *Flow_Pesos* (more than 80 percent) and is significant at 5 percent. Both *Ranking2*nd*_3*rd and *Ranking6*th*_lower* are non-significant, and the latter variable shows a negative sign. Most of the *Quantity_Flow* coefficients that are consistent with the findings of Panel A2 when *Flow_Clients* is used are definitely non-significant. In Panel D, fixed-effect models show that the ranking coefficient of 1st place in *Value_Flow* is positive, significant at 1 percent, and almost equal to that of Panel C. The other ranking variables are non-significant.

Additionally, Table 4.6–Panel E shows the percentage change in average asset value per client (total assets over total number of clients) that the 12-month performance winner fund experiences, realized through two windows. The first window, called *before-current*, computes the variation between one month before (t-1) and the current month (t0), and the second window, called *before-after*, refers to one month before (t-1) and one month after (t+1) the winner fund achieves the top place (t). Both measures are adjusted by return and merger.[79] To compare results in Table 4.6–Panel E, I add percentage change in the number of clients using the same two windows. Remarkably, the variation of average value per client is greater than that of the number of clients,

[79] It is reported only quarterly because the monthly results are identical to quarterly results through the period. The 12-month performance values arise from 1998:05.

which is consistent with the prior explanations that fund flows are explained more by movements in larger accounts than by changes in the number of clients. For instance, as of June 1998, PFA 5 increased its average asset per client by 7.7 percent and its number of clients by 1.45 percent. In the period 1998:05–2001:12, top performers exhibit a mean of the percentage change in asset value per client and number of clients of 2.11 percent and 0.23 percent, respectively, for the window of the periods (t-1) and (t+1).

In all the models discussed, the standard deviation is not a significant variable in the decision-making process of clients. A possible reason for this is that volatility is a technical concept, one that is not easily understood by clients since it would require extensive knowledge of portfolio management. Another possible explanation is that when testing differences in standard deviations in pairwise funds, I find that these differences are statistically not significant. If investors were capable of recognizing this fact, then standard deviations evidently would be irrelevant. However, these investors (the clients) are lay people—simple workers—so I hypothesize that volatility is a very specific concept that is not well understood by most clients, and at the same time, insignificant in magnitude when considered by the more investment-savvy clients and performance chasers.

4.5. WHAT DO PFAS ADVERTISE TO ATTRACT MORE FUND FLOWS?

The second question that I address is how pension funds compete to gain market share. From the previous section, I find that clients principally follow the winner fund, and I conjecture that fund strategies tend to highlight past performance, ranking position, and lower fee schemes to attract customers. As pictured in Diagram 1, when returns are realized, funds start publicizing performance in the media and through their fund vendors. However, excessive promotion through ads and vendors has two effects. On the one hand, it may overwhelm consumers, make them less sensitive to performance, and confuse them about the effective message that the pension fund wants to disclose. On the other hand, it may emphasize relevant factors such as historical performance, drops in fees, etc. that make consumers more aware of the real advantages of a specific fund. Sirri and Tufano (1998) evaluate the media attention given by positive, neutral, and bad news and use as a dependent variable the share of circulation cites. They conclude that consumers react uniformly to top and bottom performers.

I examine specifically whether and how long funds promote performance and decrease in fees and I compute the variables of marketing and salespersons of each fund normalized by the values of the industry. $Weight\_Marketing\_Tmonth_{i,t}$ is defined as the share of advertising expenses realized by PFA (*i*) for different cumulative periods (*T = 1, 3, 6 and 12 months*) over total advertising expenses incurred by the industry for the period (*T*). The other variable considered is $Weight\_Salesperson\_Tmonth_{i,t}$, the share of the number of salespersons of each fund for different cumulated months (*T = 1, 3, 6 and 12*). This variable is computed similar to the *weight_marketing*, by dividing the number of salespersons of each PFA over the total number of salespersons in the industry. The significance of these two variables over the simple variation in pesos or in percentage is that it captures the effect of the amount of a particular PFA's advertising relative to the entire PFA system's adverstising in certain period of time, since all PFAs could be increasing their advertising during that time, and hence I would be unable to distinguish which of them is doing a larger campaign. I intend to identify how important is the PFA(*i*) marketing expense in relation to the industry. Sirri and Tufano (1998) use the share of media cites and find no difference between flow-performance and funds receiving media attention, because media coverage of U.S. mutual funds has increased over time.

Results are illustrated in Table 4.7, and the models are as follow:

(4.11)

$$Weight\_Marketing\_T\,month_{i,t} = \alpha + \beta_1 LOG(Asset)_{i,t-1} + \beta_2 Standard.Deviation_{i,t} +$$
$$\beta_3 Change.Tot.Expenses_{i,t} + \beta_4 Dummy.Ranking\_12month_{i,t-2} + \varepsilon_{i,t} \qquad T = 1,3,6,12\,months$$

In Panel A, I display four regressions with Model (4.11) for four different periods of (*T*) of the dependent variable weight of marketing. I use *Ranking1st* as independent variable and logarithm of asset values, standard deviation of past-3-months returns, and change in total expenses as control variables. These models are computed under Fama-Macbeth (1973). Table 4.7–Panel B considers the four above models under fixed-effect regression. Unlike Table 4.7–Panel A, Panel C utilizes the independent variable *Ranking6th_lower* instead of *Ranking1st*. Table 4.7–Panel D exhibits results under fixed-effect as robustness with the same models of Table 4.7–Panel C.

The results of Table 4.7–Panel A show that winner pension funds tend to advertise more and their ad campaigns do not last long. Marketing efforts are highly concentrated in 1-month and 3-month periods after that the 12-month ranking winner is known. For *T=1* and *T=3*, the coefficient value of *Ranking1st* is 0.066 (at 5 percent) and 0.060 (at 10 percent). No significance is found for 6-month and 12-month periods in the weight of marketing expenses. Consistent with this evidence, Table 4.7–Panel B displays identical information. The coefficients of *Ranking1st* are 0.037 and 0.022, both significant at 5 percent. I discover in Panel C that loser funds, those ranked 6th or lower, exhibit lower expense levels in relation to the others. In fact, the ranking coefficient of poorly-performing funds is negative, meaning that the relative importance of their marketing expenses decreases with their performance. Table 4.7–Panel D shows the same conclusion. In sum, top funds advertise proportionately more than loser funds;

however, their marketing campaigns do not last beyond three months. To check this result with other funds, I define Model (4.12):

(4.12)

$$Weight\_Marketing\_3month_{i,t} = \alpha + \beta_1 LOG(Asset_{i,t-1}) + \beta_2 Standard.Deviation_{i,t} + \beta_3 Change.in.Expenses_{i,t} + \beta_4 Dummy.Ranking1^{st}\_12m_{i,t-2} + \beta_5 Dummy.Ranking2^{nd}\_3^{rd}\_12m_{i,t-2}$$

Model (4.12) in Table 4.7–Panel E considers as a dependent variable *Weight_Marketing_3month*$_{i,t}$. It is the weight of marketing expenses with three accumulated months and is run in pairwise ranking variables. Model (4.12a), with dummy variables *Ranking1*st and *Ranking6*th*_lower*, shows that the coefficient of the top fund is positive and significant at 5 percent. In contrast, loser funds tend to decrease their advertising expenses. Similarly, Model (4.12b) employs variables *Ranking1*st and *Ranking2*nd*_3*rd and exhibits that *Ranking1*st is positive, significant at 5 percent, and superior to *Ranking2*nd*_3*rd. Funds that do not reach the top position in performance expend the same share or less on marketing expenses. Table 4.7–Panel F displays the same model (4.12), but under fixed-effect, and its results support Table 4.7–Panel E's findings that funds below 1st place in the ranking spend less than the winner. No significant results are obtained when running the weight of salespersons against the same variable set used in Models (4.11) and (4.12) since the number of workers steadily falls through time and every fund tends to keep its weight. In Table 4.7–Panel G, I use the variable marketing expenses of 3 months scaled by asset value for each fund. The regressions that are run under both Fama-Macbeth and fixed-effect use as independent variables performance ranking and fee schemes as well as the same control variables employed throughout this document. The results still support the hypothesis that funds advertise top performers. The coefficient of ranking 1st place is positive and significant, and the other ranking coefficients are not significant.

Consistent with our previous findings, PFAs increase advertising in the short term. Their policies are driven by marketing efforts that increase in the period after reaching the top position, but the effect of these efforts is very ephemeral, since the next period's winner will apply the same plan. In this "spinning wheel," PFAs regularly rotate from the top to lower positions. However, the commercial strategy to hold onto market share is to advertise when one is on top. The lack of a diverse service encourages funds to principally focus their marketing effort uselessly on short-term performance because the winner is never the top performer for more than 3 periods. The transition probability of a fund's being the top fund for the next period, given that it was a winner in the past 12 months or in the past 1 month, is less than 4 percent and 7 percent, respectively.

4.6. WHAT PART OF FLOWS EXPLAINS THE DECISIONS OF CLIENTS?

To investigate the variables that are definitely relevant to consumers in selecting a pension fund, I use as control variables logarithm of asset values and the weight of the number of salespersons and run models under the four flow definitions, *Flow_Pesos*, *Value_Flow*, *Quantity_Flow* and *Flow_Clients*, characterized in Model (4.13) with the variable $Flow_{i,t}$. In this model, I use variable and fixed fees as independent regressors with a 1-month lag ($VarFee_{i,t-1}$, $FixFee_{i,t-1}$). Performance (*Premium_12m*) is measured as excess return on the benchmark lagged 3 months. Results under Fama-Macbeth (1973) are listed in Panel A of Table 4.8.

(4.13)

$$Flow_{i,t} = \alpha + \beta_1 LOG(Asset)_{i,t-1} + \beta_2 Weight\_Salespersons\_3month_{i,t} + \beta_3 VarFees_{i,t-1} + \beta_4 FixFees_{i,t-1} + \beta_5 Premium\_12month_{i,t-3} + \varepsilon_{i,t}$$

The evidence confirms a positive and significant relationship between flow and past performance, consistent with other studies.[80] An increase of 10 basis points in

[80] Huang *et al*. (2003), Shu *et al*. (2002), Sawicki (2001), Sirri and Tufano (1998), Chevalier and Ellison (1997) and Ippolito (1992).

premium could drive fund flows to move up 3.3 percent. Fees and premiums are highly significant at 5 percent. The coefficients of the fixed fee and variable fee variables in the regression *Flow_Pesos* are explained importantly by the value of the same coefficients in *Value_Flows*. The fixed fee coefficient in *Flow_Pesos* is 88 percent explained by the value of the fixed fee coefficient obtained from *Value_Flow*. Likewise, the variable fee coefficient in *Flow_Pesos* is 77 percent explained by the variable fee coefficient obtained from *Value_Flow.* Finally, the premium coefficient in *Flow_Pesos* is 61 percent explained by the premium coefficient obtained from *Value_Flow*. *Quantity_Flow* has no significant values. Although the independent variables exhibit appropriate signs and lower coefficients than those of *Value_Flow*, none of them is statistically significant to explain changes in the flow of clients.

The interpretation of this finding is that an important segment of the clients is sensitive to neither past performance nor fee reductions since the benefit offered by the system is the same across pension funds. Past performance is similar among funds, so it is not a relevant characteristic. Clients tend to pick randomly and stay steadily in a PFA. Another possible explanation for findings is that the net inflow/outflow of clients in each fund is zero, but not the inflow/outflow of money. In effect, because there is no cost to transfer from one fund to another, certain clients, usually with large amounts in their saving accounts, tend to pay more attention to fees and past performance, and they are the ones who generate the net inflow of money. In terms of benefits, it would be more profitable for pension funds to use a reduction in the fixed fee as a competitive element since this accounts for 20 percent of fee revenues and has about the same impact on flows as a reduction in the variable fee. However, in reality, funds get involved in price wars through variable fees.

Unlike the previous model, Model (4.14) incorporates the variable *Ranking_12m* lagged 3 months and removes *Premium_12m*.

(4.14)
$$Flow_{i,t} = \alpha + \beta_1 LOG(Asset)_{i,t-1} + \beta_2 Weight\_Salespersons\_3month_{i,t} + \beta_3 VarFees_{i,t-1} + \beta_4 FixFees_{i,t-1} + \beta_5 Ranking\_12month_{i,t-3} + \varepsilon_{i,t}$$

Table 4.8–Panel B still shows that certain consumers are fee chasers and top-performance chasers. *Ranking_12m* is highly significant at 1 percent and negative (1 being the highest score, 13 the lowest). Negative and significant coefficients in both fixed and variable fees are found. Clients with larger savings accounts particularly drive the variation in flows. I am unable to give evidence that any change in flows is generated by flocking of clients. Given the definition of flows, *Flow_Clients* produces the same coefficient values as *Quantity_Flow* and none of these values is statistically significant. Model (4.15) considers variables *Ranking1st* and *Ranking6th_lower* and its outcomes are shown in Table 4.8–Panel C. Model (4.16), not shown, includes the variables *Ranking1st* and *Ranking2nd_5th*. Fund vendors are not relevant to luring fund flows.

(4.15)
$$Flow_{i,t} = \alpha + \beta_1 LOG(Asset)_{i,t-1} + \beta_2 VarFees_{i,t-1} + \beta_3 FixFees_{i,t-1} + \beta_4 Ranking1^{st}\_12month_{i,t-3} + \beta_5 Ranking6^{th}\_lower\_12month_{i,t-3} + \varepsilon_{i,t}$$

Table 4.8–Panels C and D support the idea that fund flows definitely tend to move toward winning performers. In contrast, institutions classified between 2nd place and 5th place tend not to receive flows, *ceteris paribus*. Poorer funds ranked between 6th and the bottom positions see their flows fly away. These findings prove the flow-performance relationship is not linear. Consumers disregard poorly-performing funds and exclusively allocate their resources into winner funds. *Value_Flow* is the driver of changes in flows. Results obtained using the fixed-effect model are consistent with the Fama-Macbeth procedure (not listed). To evaluate the effect of fund vendors, I run four regressions with the dependent variable *Flow_Pesos* and the independent variables log(assets),

performance, marketing expenses, fees, and the number of salespersons. Results are shown in Table 4.8–Panel E. The salespersons variable is represented by: (i) the share of number of vendors of fund (i) over the total vendors in the industry (weight_salesforce); (ii) the number of salespersons scaled by asset value of each fund; (iii) the number of salespersons normalized by the number of clients of each fund; and (iv) the cumulative average of the number of vendors for 3 months.

Table 4.8–Panel F shows results from running a regression similar to Table 4.8–Panel E's regressions but without performance as a regressor. In both panels under fixed-effect, the number of vendors is not significant, and past performance measured as ranking 1st place, 12-month premium, and 12-month ranking is still highly significant.[81] The most plausible explanation of this result is that, as mentioned earlier, the number of salespersons consistently diminished in the period across PFAs; hence, this variable does not convey any additional information to the model. To find out if flows are sensitive to a seasonality variable, I test it using dummy and interaction variables per quarter. The results show no significance in any dummy variable DQ(i), which seems consistent with the mandatory contribution required by law. Unlike mutual fund investors, pension fund clients must regularly make monthly payments to their saving accounts, regardless of the financial performance of PFAs.

In sum, the dependent variable advertising expenses of PFA (i) scaled by total advertising expenses of the industry (*weight_marketing*) demonstrates that PFAs essentially advertise winner funds and lower fees. When this variable is normalized by the asset value, a similar conclusion is displayed. However, I think the first definition of the marketing expenses variable better explains the findings for two reasons. First, if all PFAs increase their advertising by 10 percent, then *weight_marketing* does not change,

[81] The Fama-Macbeth (1973) procedure provides the same results in Panels E and F. I show the fixed-effect model because it tends to display higher t-values than the Fama-Macbeth method.

but if this variable is scaled by assets, it would increase in value. If PFA (i) increases its marketing activities by 10 percent and PFA (j) does so by 5 percent, then *weight_marketing* of fund (i) would go up. Second, if the number of clients constantly rises through periods, then the same amount of marketing expenses spent by the PFAs would decrease if scaled by assets or clients. However, *weight_marketing* tends to capture what others are doing. As PFAs tend to look at each other in their investment style, as previously documented, then the same argument may be applied to marketing strategy. In fact, although all PFAs systematically decreased the number of vendors, the correlation between *weight_marketing_3months* (the share of advertising expense of fund (i) over the industry's advertising expenses) and *weight_salespersons_3months* (the share of the number of salespersons of fund (i) over the industry's salespersons) is 0.73 for all PFAs and 0.65 for the three leaders. I infer, then, that PFAs have tried to hold their relative importance in marketing expenditures and number of vendors, and the winner fund advertises more.

4.7. WHY DOESN'T VOLATILITY MATTER?

In this study, volatility does not play an important role. I evaluate the differences in standard deviation of 12-month performance in fund pairs and find that the differences are not statistically significant. Funds exhibit not only similar returns but also similar standard deviation. However, Brown, Harlow, and Starks (1996), Chevalier and Ellison (1997), and Huang, Wei, and Yan (2003) argue that fund managers who perform poorly and are behind in the rankings tend to increase the return volatility in the following periods as a mechanism to get out from the bottom position. Implicitly, managers have a call option-like compensation. As evidenced in this document, even though clients chase top performers, poorer fund managers do not alter their portfolio risk. Unlike mutual funds in the U.S., Taiwan, and Australia, the Chilean pension fund legislation requires that all funds must return at least the weighted average return minus 2 percent, or minimum guaranteed return (MGR); otherwise, PFAs must supplement the difference between the current return and the MGR. As the MGR is based on peer relative performance, managers tend to copy each other's portfolio choices. In this setting, the penalty for behaving differently from others is so onerous that managers rarely deviate from others and essentially are encouraged to pursue short-term portfolio strategies that realize similar returns and volatility. Increasing volatility may drag the manager's performance way below the MGR. In other words, the explicit punishment dramatically outweighs the implicit incentive to reach better positions by raising the portfolio risk. The contract offered to Chilean pension managers is not call option-like as it is in U.S. mutual funds.

4.8. WINNER PERSISTENCE

Do winner fund repeat through time? The market efficiency hypothesis claims that no trader is able to earn abnormal returns based on available information. Unlike a single investor, mutual and pension fund managers constantly conduct research in search of investment opportunities that provide higher performance. Several U.S. studies have documented that money managers try to outperform the benchmark or their peers as evidence of the managers' ability. The classic and pioneering study of Jensen (1968) reveals that mutual fund managers do not perceive better returns than the market, after subtracting fees. Likewise, Brinson, Hood, and Beebower (1986), analyzing 91 U.S. pension funds, find that on average, managers underperform the passive benchmark. Lakonishok, Shleifer, and Vishny (1992) argue that not only do pension fund managers subtract value because their performance is 1.3 percent below the annual S&P 500's, but they also lack annual performance consistency. In contrast, Grinblatt and Titman (1989, 1992) and Hendricks, Patel, and Zeckhauser (1993) confirm a persistent level of abnormal performance by mutual funds. Zheng (1999) postulates that investors may be better off if they take of advantage of short-term performers' persistence. Goeztmann and Ibbotson (1994) suggest that monthly returns are consistent with the repeat winner hypothesis and that investors should follow historical fund rankings to obtain superior returns. These authors do not measure whether funds outperform some index but rather how funds rank with respect to one another. They categorize funds as winners or losers if they are above or below the median performance for each interval period. They run regressions on each fund's rank against its prior month's rank and conclude not only that the earlier month's ranking has the power to predict the next month's ranking but also that R-square is small because the monthly returns are noisy.

I label a winner fund with a value of 1 when it is exclusively ranked in first place on the past performance in periods of 1-, 3-, 6-, 9- and 12-months and 0 otherwise. Table 10 displays the frequency of each PFA in getting the top position in the ranking for different periods. In the case of 1-month performance with 55 periods, only two funds never reached the top position; PFA 6 obtained the highest frequency with almost 24 percent (13 times). However, when I calculate the frequency that a PFA is winner in two consecutive months, the number of outcomes is only 9, and PFA 6 comes out on top in 3 opportunities. During the first year (1997:06–1998:06), with all funds competing, PFA 6 never got the first place[82]. The transition probability of being a winner PFA at T_1 is 7.6 percent. This is divided into the probability of being top performer at T_1 (given that the PFA was a winner fund at T_0 is 16.6 percent) and the probability of being top performer at T_1 (given that the PFA was not a winner fund at T_0 is 6.9 percent). If this transition probability is computed for the period 1999:01–2001:12, the likelihood of being winner at T_1 (given that the PFA was a winner fund at T_0) is smaller, 14.3 percent. I run the

[82] Keep in mind that the pension funds system functioned with 8 funds from 1999:01.

regressions for individual funds of the 1-month ranking on one lag 1-month return ranking, and the largest R^2 obtained is 0.29. These results tend to support the notion of the absence of monthly winner persistence. If the differences in monthly performance are non-significant, one could expect the top fund position to be random.

When other periods are analyzed, individual regressions of 12-month return ranking on prior 12-month return ranking exhibit the greatest R^2, which is equal to 0.59[83]. In terms of frequency, none of funds that ranked 4th place or lower ever reached the 1st place. This result is biased by the fact that from 1999:01, the sample is composed of only 8 PFAs. The transition probability of remaining in 1st, 2nd, 3rd, 4th, 5th, 6th and 7th in two consecutives months is 74, 46, 43, 32, 41, 51 and 42 percent, respectively. The same four PFAs usually achieved the top position. Although PFA 6 (small fund) and PFA 9 (leader fund) were most frequently ranked as the rolling 12-month winner fund, PFA 6 plunged to the lowest position for several consecutive months after being in 1st place for numerous consecutive months. In fact, the average ranking of 12 months for PFA 6 and PFA 9 is 3.4 and 3.8, respectively. The second largest fund (PFA 5) accounts for 3.5 with a standard deviation in ranking very similar to the leader's. Medium size funds average 5.0, while small and some defunct PFAs average 4.2 and 5.3, respectively. These findings are consistent with the hypothesis that winner funds are not persistent and that medium, small, and defunct funds tend to follow the leaders. The leaders have been in 1st, 2nd, or 3rd places more often than other funds, as evidenced by their average ranking value.[84]

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[83] Coefficients range between 0.00 and 0.77. The zero value is due to two survivor funds never getting the top position.

[84] Olivares (2003) finds that medium, small, and defunct funds tend to mimic the investment strategy followed by the three largest funds.

4.9. Concluding Remarks

Variations in flows of Chilean pension funds are studied in this paper. The flow definition is split in two parts; value and quantity, to capture whether changes in flows are driven by larger account size or by the number of clients. I investigate the predominant variables that are considered by clients in order to select a pension fund as well as the marketing strategy followed by funds in order to compete and gain market share. I find a positive relationship between flows and past performance, measured by 12-months excess return. However, this relationship is not linear. Consumers allocate their savings into the funds ranked in the top position, while the funds that are considered poorer performers lose flows. Variable and fixed fees are also important. The variation in flows is almost identical when both types of fees decrease by the same percentage. However, although the contribution of variable fees to total revenues is larger than that of fixed fees, pension funds compete aggressively based on variable fees. Although I do not appreciate net changes in the number of clients driven by performance and fees due to a new amendment restricting transfers, fund flows are moved principally by investors with larger accounts who care about top performers and fee reductions. The component *Value* explains basically the changes in flows. This provides evidence of the existence of two groups of investors. Investors in the first group, who have large accounts, seem to recognize that the small differences in returns are important and therefore move their monies into better-performing funds. In contrast, investors in the other group tend to hold their monies in the same pension fund even when it performs poorly. For them, it is not really important to move their monies out of poor funds, because they consider the tiny differences in return to be non-relevant and believe that the winner in this tournament rotates over time, so they think they will achieve the average return through time. Essentially, for this group of clients, performance does not matter.

In relation to marketing strategy, funds focus their plans on past performance. I find evidence that funds in the bottom position tend to reduce their marketing expenses relative to other funds. Winner funds increase their advertising expenses, stressing their ranking in ads. I find that marketing campaigns are designed to last three months, at most, because the winner fund in the ranking is random through periods. Funds do not significantly change their market share. Over time, the only significant element for gaining market share has been mergers. Defunct funds were not able to attain the break-even point and hence exhibited permanent net operating losses despite their commercial efforts to draw more clients.

I find that volatility is not important. The emerging question is why poorly-performing funds don't alter their portfolio risk. The answer rests on the penalty imposed by the SPFA on funds that do not achieve a minimum return. Managers' compensation is not call option-like, but financial future-like.

In sum, based on my results, some consumers react asymmetrically to past returns and positively to fee reductions. The current legislation provides a special setting that induces funds not to differentiate from each other. Not only are their returns similar, but their marketing strategies are, too. Fund management service may be seen as a commodity: all funds give the same product (returns) at the same price (fees). I believe the Chilean market does not encourage competition but rather complacency among funds. No pension fund is hurt if investment and marketing strategies are replicated. Fund managers are afraid to be seen as different from each other, and the conformity to be over the MGR floor is a sign of survivorship. At first glance, they look like competitors but in fact they need each other.

Appendices

Table 2.1. General Description of Chilean Pension Funds

(As of December of each year)

The number of pension fund managing companies (PFAs) decreased during the period 1994–2001 as a result of 11 mergers and 3 license cancellations due to insufficient margin accounts. Fund values are expressed in both US$ millions and as a percentage of Chilean GDP. Annual Real Return corresponds to the PFA system return deflated by the annual inflation rate. The market share is measured by fund assets value represented by the Herfindahl index and the market proportion of the three largest PFAs (Larger 3) and the market share of the smallest three PFAs (Smaller 3). Herfindahl index is a measure of market concentration and is calculated by squaring the market share of each PFA and then summing those squares. The market share is obtained from asset values of each fund divided by total assets value of the industry.[85]

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[85] Herfindahl Index is defined in Tirole (1988) as $\sum_{i=1}^{n} \alpha_i^2$ where α_i^2 is squared market-share of fund (*i*).

Table 2.1. General Description of Chilean Pension Funds
(As of December of each year)

Year	Number of PFAs	Funds Value (million Chilean $)	Funds Value (million US $)	Funds (as % of GDP)	Annual Real Return	Herfindahl Index	Market Share of 3 Larger Funds	Market Share of 3 Smaller Funds
1981*	12	35,520	296	0.8	12.8	0.217	71.3	1.8
1982	12	127,600	941	3.3	28.5	0.194	67.6	3.0
1983	12	261,101	1,704	5.9	21.3	0.180	65.7	4.6
1984	12	390,275	2,254	7.7	3.6	0.174	65.4	4.9
1985	11	607,319	3,104	10.0	13.4	0.179	65.8	5.0
1986	12	897,634	4,060	12.7	12.3	0.182	66.6	3.3
1987	12	1,243,175	4,976	14.2	5.4	0.178	66.6	3.5
1988	13	1,719,566	6,091	15.0	6.5	0.172	66.3	2.8
1989	13	2,396,109	7,511	17.7	6.9	0.167	65.3	3.2
1990	14	3,332,381	9,948	24.2	15.6	0.158	62.6	2.1
1991	13	5,232,683	14,069	31.4	29.7	0.147	59.0	3.6
1992	19	5,960,709	15,677	30.6	3.0	0.136	56.6	0.2
1993	20	8,578,034	20,149	37.0	16.2	0.130	54.4	0.2
1994	21	9,781,027	24,317	41.0	18.2	0.125	52.7	0.5
1995	16	10,571,724	25,849	38.8	-2.5	0.131	51.8	1.4
1996	13	11,570,655	27,392	39.5	3.5	0.134	53.8	2.3
1997	13	13,359,517	30,481	38.6	4.7	0.139	55.6	1.9
1998	9	14,509,931	30,716	39.8	-1.1	0.169	62.0	5.2
1999	8	18,453,949	34,287	48.6	16.3	0.208	70.4	5.6
2000	8	20,406,835	35,513	50.2	4.4	0.207	70.2	6.0
2001	7	23,389,120	34,954	54.3	6.7	0.209	70.5	16.6

Source: Superintendence of Chilean Pension Funds, *The Chilean Pension System,* 1999.
*The system started in May of 1981. For that year, the return is annualized.

Table 2.2. Returns Distribution of PFA System

The table provides information on the monthly return achieved by the pension funds system. As a way of not overwhelming the reader, I list this monthly information every three month. Average return is the simple average of funds group. Standard deviation is calculated for each month across funds. Maximum and Minimum returns correspond to cross-sectional values for each period. Differences in returns are exhibited for (Maximum – Minimum), (Largest fund return – Simple Average) and (Medium Fund return – Simple Average).

Table 2.2. Returns Distribution of PFA System

Date	Average Return (%)	Standard Deviation (%)	Maximum Return (%)	Minimum Return (%)	Difference Max-Min (%)	Difference Largest Fund-Average (%)	Difference Medium Fund-Average (%)
Jun-97	2.52	0.11	2.68	2.34	0.34	0.07	-0.03
Sep-97	-0.05	0.09	0.09	-0.19	0.28	0.06	-0.05
Dec-97	-0.39	0.16	0.04	-0.61	0.65	0.11	0.05
Mar-98	3.07	0.15	3.35	2.84	0.52	0.14	-0.03
Jun-98	-1.87	0.15	-1.60	-2.14	0.53	0.07	0.04
Sep-98	-3.79	0.36	-3.18	-4.25	1.07	0.17	0.25
Dec-98	-0.06	0.09	0.07	-0.21	0.28	0.13	0.08
Mar-99	1.56	0.16	1.90	1.41	0.48	-0.18	0.00
Jun-99	2.26	0.16	2.52	2.05	0.48	0.48	0.25
Sep-99	0.87	0.08	0.97	0.77	0.21	0.14	0.17
Dec-99	1.16	0.15	1.37	1.00	0.37	0.00	-0.20
Mar-00	1.15	0.13	1.29	0.88	0.41	-0.13	-0.03
Jun-00	1.78	0.12	1.94	1.57	0.37	-0.18	-0.03
Sep-00	-0.27	0.13	-0.07	-0.38	0.30	0.13	0.10
Dec-00	0.60	0.03	0.65	0.55	0.11	0.06	-0.02
Mar-01	0.19	0.11	0.35	0.06	0.29	-0.03	0.16
Jun-01	0.96	0.17	1.31	0.80	0.51	-0.06	-0.11
Sep-01	-0.22	0.28	0.32	-0.43	0.75	0.01	-0.01
Dec-01	0.10	0.09	0.22	-0.04	0.26	-0.08	0.11
Avg.*	0.01	0.00	0.01	0.01	0.00	0.00	0.00
St. Dev.*	0.02	0.00	0.02	0.02	0.00	0.00	0.00

Source: Superintendence of Pension Funds.
*Average and Standard Deviation are calculated on the whole data.

Table 2.3. Limits on Investments of Pension Funds

With regard to the diversification of pension funds, the Pension Funds Act legislation sets the maximum percentages of resource allocation that a PFA may invest in. These percentages are defined in relation to (i) issuer, (ii) issuer related to PFA's ownership and management, (iii) individual financial asset, (iv) asset groups, and (v) exposure to specific risks. According to the Pension Funds Act, these limits are presented as alternatives between lower and upper boundaries. The Central Bank of Chile is in charge of determining the final value of these limits. During the period 1981–2000, the legal framework authorized PFAs to manage just one fund (Type I); however, after the 2000 amendment, theses institutions were allowed to address two funds (Type I and Type II). In the latest modification to the legislation (August 2002), the Superitendence of Pension Fund Administrators (SPFA) allowed PFAs to handle five funds instead of two as a way to augment the diversity of portfolios.

Table 2.3–Panel A. Limits by Securities (Period: 1981-2000)

Security	Lower-Upper Margin Proposed in the Act (as % of Pension Fund)*	Maximum Limit Defined by Central Bank of Chile (as % of Pension Fund)
Government bonds	35 - 50	50
Deposits in banks & bank bonds	30 - 50	50
Mortgage-backed securities issued by banks	35 - 50	50
Corporate & convertible bonds	30 - 50	45
Convertible bonds (alone)	10 - 15	15
Corporate stocks & REIT shares	30 - 40	37
Mutual funds shares	5 - 10	5
Foreign assets and hedge	6 - 12	12
Foreign currency hedge in domestic market	5 - 15	12

Source: Superintendence of Chilean Pension Funds, *The Chilean Pension System,* 1999.

*The Central Bank is the technical institution that sets the limit values proposed by the law.

Table 2.3–Panel B. Limits by Securities (as of 2001)

Security	Fund Type I Lower-Upper Margin (%)	Fund Type II Lower-Upper Margin (%)
Government bonds	35 - 50	50
Deposits & bank bonds	35 - 50	50
Mortgage-backed securities issued by banks	35 - 50	50
Corporate & convertible bonds	35 - 50	45
Convertible bonds (alone)	35 - 50	15
Stocks and REIT notes	30 - 45	37
Mutual funds shares	15 - 35	5
Foreign assets and hedge	10 - 20	12
Foreign currency hedge	10 - 25	12

Source: Superintendence of Chilean Pension Funds, *The Chilean Pension System,* 1999.

Table 2.3–Panel C. Limits by Issuer* (Period: 1981-2000)

The maximum percentage that Pension Funds are allowed to invest in financial assets guaranteed by a single issuer	Margin in % (as % of Pension Fund)
Leasing Company Bonds:	The lowest among the three criteria:**
	(a) 7% Pension Funds x factor (iv)
	(b) 20% of new issuance or
	(c) Issuer's Equity x factor (vi)
Corporate Stocks:	The lowest among the three criteria:**
	(a) 5% Pension Funds x factor (i) x factor (iii) or
	(b) 7% of issued stocks or
	(c) 20% of new issuance

Source: Superintendence of Chilean Pension Funds.

*In this case, there was no change in limits like there was for limits by financial instrument. The purpose of this provision is to control the concentration of funds by constraining this percentage.

**In the case of Leasing Company Bonds, factor (iv) refers to *weighted risk* previously defined.

Table 2.4. Holdings of Chilean Pension Funds

The portfolio has been divided into 9 asset classes. The summation of weights is equal to 1.0. Securities were introduced into the portfolio of Pension Funds little by little by the economic authority concerned with monitoring the good development of a new system. In fact, the holdings were initiated with four assets. Stocks became suitable assets in 1985. Both mutual funds and foreign securities did so in 1992.

Year	Gvt. Bonds	Banking Deposits	Mortgage Securities	Banks Bonds	Corporate Stocks	Corporate Bonds	Mutual Funds	Foreign Securities	Cash
1981	28.1	61.9	9.4	0.0	0.0	0.6	0.0	0.0	0.0
1982	26.0	26.6	46.8	0.0	0.0	0.6	0.0	0.0	0.0
1983	44.5	2.7	50.7	0.0	0.0	2.1	0.0	0.0	0.0
1984	42.1	12.2	42.9	0.6	0.0	1.8	0.0	0.0	0.4
1985	42.4	20.4	35.2	0.4	0.0	1.1	0.0	0.0	0.5
1986	46.6	22.9	25.5	0.3	3.8	0.8	0.0	0.0	0.1
1987	41.4	27.4	21.3	0.7	6.2	2.6	0.0	0.0	0.4
1988	35.4	28.5	20.6	1.0	8.1	6.4	0.0	0.0	0.0
1989	41.6	20.8	17.7	0.7	10.1	9.1	0.0	0.0	0.0
1990	44.1	16.3	16.1	1.1	11.3	11.1	0.0	0.0	0.0
1991	38.3	11.7	13.4	1.5	23.8	11.1	0.0	0.0	0.2
1992	40.9	9.4	14.2	1.6	24.0	9.6	0.2	0.0	0.1
1993	39.3	6.1	13.1	1.4	31.8	7.3	0.3	0.6	0.1
1994	39.7	4.8	13.7	1.6	32.1	6.3	0.9	0.9	0.0
1995	39.4	5.3	15.8	2.0	29.4	5.3	2.6	0.2	0.0
1996	42.1	4.2	17.9	2.5	25.1	4.7	3.0	0.5	0.0
1997	39.6	10.7	17.0	2.5	22.6	3.3	3.1	1.2	0.0
1998	41.0	13.6	16.6	1.8	14.5	3.8	2.9	5.6	0.1
1999	34.6	16.1	15.1	2.5	11.9	3.8	2.6	13.4	0.0
2000	35.7	18.7	14.4	2.5	11.1	4.0	2.4	10.9	0.2
2001	35.0	17.5	12.9	2.7	10.0	6.2	2.4	13.4	0.0

Source: Superintendence of Chilean Pension Funds.

Table 3.1. Descriptive statistics of Chilean pension funds

Table 3.1–Panel A. Number of Clients and Total Revenues and Expenses

Date	Clients*	PFA Employees	Total Incomes (Chilean $ Millions)	Total Expenses (Chilean $ Millions)	Total Incomes (US $ Millions)	Total Expenses (US $ Millions)
Jun-97	5,653,223	44,761	144,845	113,121	347	271
Sep-97	5,714,689	44,284	211,184	173,843	509	419
Dec-97	5,780,400	39,841	282,697	239,306	645	546
Mar-98	5,825,969	28,417	77,383	55,661	171	123
Jun-98	5,843,492	25,066	140,050	113,591	307	249
Sep-98	5,869,622	20,508	189,141	165,146	402	351
Dec-98	5,966,143	17,141	276,821	228,164	586	483
Mar-99	5,984,508	13,502	80,767	54,173	164	110
Jun-99	5,995,985	12,993	162,201	108,469	323	216
Sep-99	6,055,176	12,139	233,425	163,660	445	312
Dec-99	6,105,731	11,065	311,629	221,208	579	411
Mar-00	6,132,650	10,572	78,179	50,438	155	100
Jun-00	6,153,988	10,047	153,625	100,121	290	189
Sep-00	6,240,213	10,082	229,190	152,793	405	270
Dec-00	6,280,126	9,716	357,420	212,038	622	369
Mar-01	6,307,923	8,877	85,230	49,962	145	85
Jun-01	6,331,109	8,776	168,187	101,652	273	165
Sep-01	6,387,603	8,906	244,565	154,641	359	227
Dec-01	6,427,391	8,868	327,209	212,787	489	318

Source: Superintendence of Chilean Pension Funds.

Note: The values are represented in Chilean pesos and dollars only to make it easier for readers to understand the amounts. However, the data is worked in Chilean pesos.

*The Pension Fund Act uses the term *affiliates* to refer to pension fund contributors or clients.

Table 3.1–Panel B. Number of Pension Fund Institutions and Average Return

Date	Number of PFAs	Average Return (%)	Maximum Return (%)	Minimum Return (%)
Jun-97	13	2.52	2.68	2.34
Sep-97	13	-0.05	0.09	-0.19
Dec-97	13	-0.39	0.04	-0.61
Mar-98	13	3.07	3.35	2.84
Jun-98	12	-1.87	-1.60	-2.14
Sep-98	10	-3.79	-3.18	-4.25
Dec-98	9	-0.06	0.07	-0.21
Mar-99	8	1.56	1.90	1.41
Jun-99	8	2.26	2.52	2.05
Sep-99	8	0.87	0.97	0.77
Dec-99	8	1.16	1.37	1.00
Mar-00	8	1.15	1.29	0.88
Jun-00	8	1.78	1.94	1.57
Sep-00	8	-0.27	-0.07	-0.38
Dec-00	8	0.60	0.65	0.55
Mar-01	7	0.19	0.35	0.06
Jun-01	7	0.96	1.31	0.80
Sep-01	7	-0.22	0.32	-0.43
Dec-01	7	0.10	0.22	-0.04

Source: Superintendence of Chilean Pension Funds.

Table 3.2. How Much the Variability Return is Explained by the Benchmark

To test how much the weighted average return explains the PFA performance, I divide the samples into 6 groups. Group 1 consists of the three large funds; Group 2, the two medium funds; Group 3, the two small funds; Group 4, the seven funds that survive the full period; Group 5, the three funds that have acquired other institutions and have survived; and Group 6, the six funds that were acquired and did not survive. I study Groups 1, 2, 3, 4, and 5 for the whole period (55 months) and Group 6 for the periods corresponding to the Asian (1997:06–1998:01) and Russian (1998:05-1998:11) crises and the period during which only 7 funds stayed in the market, i.e., from the last acquisition of a fund (2001:02–2001:12).

The model used is $\mathrm{Re}\,tPFA_{i,t} = \alpha + \beta_i * \mathrm{Re}\,tBenchmark_t + \varepsilon_{i,t}$ where $RetPFA_{\ i,t}$ is the return of fund groups (i) during time (t). The independent variable is the weighted average return, $RetBenchmark_{,t}$. The regression is run not only for each fund group for each period defined but also for individual funds to detect difference across funds. Panel A displays R^2 and the beta coefficient and Panel B the R^2.

Table 3.2–Panel A. Variability in Individual Funds

PFA	R^2 per Funds 1997:06 -1998:06	Beta Coefficient per Funds 1997:06 -1998:06	R^2 per Survivor Funds*	BetaCoefficient per Survivor Funds*
Aporta	0.997	1.015	---	---
Bansander	0.994	1.022	---	---
Cuprum	0.997	1.006	0.994	1.048
Fomenta	0.987	0.970	---	---
Habitat	0.999	0.974	0.997	0.983
Magister	0.996	1.043	0.986	1.063
Planvital	0.999	1.012	0.997	1.000
Proteccion	0.999	1.036	---	---
Provida	0.997	0.963	0.997	0.943
Qualitas	0.965	0.930	---	---
SantaMaria	1.000	1.011	0.999	0.998
Summa	0.998	1.013	0.997	1.040
Union	0.999	1.111	---	---
Average	0.994	1.008	0.995	1.011
Standard Deviation	0.009	0.044	0.004	0.042

*Survivor funds are the PFAs that have remained for the whole period.

Table 3.2–Panel B. R^2 of Fund Groups

Group¤	Whole period	Period 1997:06 - 1998:01	Period 1998:08 - 1998:11	Period 2001:02 - 2001:12
Group 1 - Large Funds	0.993	0.994	0.993	0.994
Group 2 - Medium Funds	0.997	0.998	0.998	0.998
Group 3 - Small Funds	0.989	0.987	0.99	0.985
Group 4 - Survivor Funds	0.993	0.993	0.993	0.983
Group 5 - Funds Acquirers*	0.99	0.987	0.989	0.987
Group 6 - Acquired Funds	0.990(a)	0.990(b)	0.990(c)	--(d)

¤From 2001:02 the system possesses 7 pension funds, the three large funds (Provida, Habitat, Cuprum), two medium funds (SantaMaria, Summa) and two small funds (Magister, Planvital). This partition is given by the fund asset values of each fund.

*This group is composed of the largest pension funds, one medium fund, and one small fund that absorbed others PFAs.

(a) The first acquisition was in 1998:05. We count up to this period as a whole period.

(b) Includes the six acquired pension funds for this period.

(c) Counts on the three acquired funds that survived during this period.

(d) No acquired funds present for this period.

Table 3.3. Differences among PFAs' Asset Allocation Weights

The asset allocation is split into five categories: stocks, bonds, banking deposits, MBS (included REIT shares), and foreign securities (as bonds and shares). The null hypothesis I test is "Beta coefficients of asset allocation weights among the pension funds are equal," i.e., $H_0 : \beta^{PFA(i)}_{asset(a)} - \beta^{PFA(j)}_{asset(a)} = 0 \ \ with\, i \neq j \ \ \ i, j = 1, 2...13 \ \ \ k = 1,...5$. The three regression models used to test it are:

Model (3.2)

$$[RetPFA_{i,t} - RetBenchmark_t] = \sum_{a=1}^{5} \beta_{i,a}[WeightPFA_{i,t-1,a} - WeightBenchmark_{t-1,a}] \ + \varepsilon_i$$

Model (3.3)

$$Return_{i,t} = \alpha + \sum_{a=1}^{4} \beta_{i,a}[AssetWeightPFA_{i,t-1,a}] + \varepsilon_i$$

Model (3.4)

$$(4)\ [RetPFA_{i,t} - RetAverage_t] = \sum_{a=1}^{5} \beta_{i,a}[WeightPFA_{i,t-1,a} - WeightAverage_{t-1,a}] + \varepsilon_i$$

The econometric procedure used is to run the regressions for one pension fund, and after doing so, run it for the rest of the funds. The Chow Test lets us identify whether any structural change has affected a pension fund or a subgroup. I compute the sum of squared errors in each regression to see if there exists evidence of changes in the coefficients between two funds and two subgroups. Each panel contains the results of the Chow test value and its F-Test. I list in panels the findings using these models.

Panels A and B exhibit the outcomes for each PFA using Models (3.2) and (3.3). When a fund is absorbed by another one, the regressions are run until the end of its date of existence and counting only the existing funds. The length of the evaluation period for each fund is different since the number of institutions shrinks with acquisitions. In fact, the first acquisition was in 1998:05; the evaluation period is 12 months for thirteen PFAs.

The second acquisition was in 1998:08; the evaluation period is 15 months for twelve PFAs. At the end, the seven surviving funds are evaluated from 1997:06 to 2001:12. The PFAs are listed according to acquisition occurrence. The first six were acquired, and the rest stayed in the market. Panel C illustrates the situation for the group of PFA acquisitions. I consider PFAs acquired and PFA buyers as subgroups. Findings of Model (3.2) are displayed. Panel D presents an analysis by periods of one year and 6 months using Model (3.2). Panel E indicates the results for the category of PFA size using Model (3.4). The subgroup is large, medium, and small.

Table 3.3–Panel A. Asset Allocation Weights—Model (3.2), All Funds

PFA[¤]	Chow Test Value	F-Test Significant at:
Union	2.8	2.82%
Bansander	3.19	1.50%
Qualitas	12.55	0.00%
Fomenta	1.57	18.40%
Proteccion	1.14	38.00%
Aporta	1.44	21.80%
Cuprum*	1.83	12.20%
Habitat*	2.97	1.90%
Magister*	2.81	2.50%
Planvital*	0.32	82.00%
Provida*	1.05	37.80%
SantaMaria*	0.39	81.10%
Summa*	0.87	48.10%

[¤]The pension funds are listed in order of first to last in the market.

*These seven PFAs have existed for the whole period 1997:06 - 2001:12.

Table 3.3–Panel B. Asset Allocation Weights—Model (3.3), All Funds

PFA[¤]	Chow Test Value	F-Test Significant at:
Union	0.79	53.1%
Bansander	0.64	63.4%
Qualitas	0.50	73.8%
Fomenta	1.22	30.6%
Proteccion	0.82	51.7%
Aporta	1.63	16.6%
Cuprum*	0.63	63.9%
Habitat*	2.00	9.4%
Magister*	2.16	7.3%
Planvital*	0.65	62.7%
Provida*	0.93	44.6%
SantaMaria*	1.28	27.8%
Summa*	1.02	39.8%

[¤]The pension funds are listed in order of first to last in the market.

*These seven PFAs have existed for the whole period 1997:06 - 2001:12.

Table 3.3–Panel C. Asset Allocation Weights—Model (3.2), Mergers

PFA Buyer - PFA Acquired	Chow Test Value	F-Test Significant at:
Provida - Union	1.08	0.4
Summa - Bansander	0.58	0.7
Magister - Qualitas	0.08	1.0
Aporta - Fomenta	1.50	0.2
Provida - Proteccion	0.63	0.6
Magister - Aporta	0.93	0.5

Table 3.3–Panel D. Asset Allocation Weights—Model (3.4), Survivor Funds

PFA	Chow Test Value	F-Test Significant at:
Cuprum	2.20	0.1
Habitat	2.37	0.0
Magister	2.24	0.1
Planvital	0.30	0.9
Provida	0.84	0.5
SantaMaria	0.32	0.9
Summa	0.69	0.6

Table 3.3–Panel E. Asset Allocation Weights—Model (3.3), Changes by Period

Periods	Chow Test Value	F-Test Significant at:
1997:06-1998:05	0.95	43.5%
1998:06-1999:05	1.06	38.0%
1999:06-2000:05	1.89	11.9%
2000:06-2001:12	0.81	52.0%

Table 3.4. Correlations of Asset Allocation Weights among PFAs

The correlation among PFAs is measured against the benchmark, which corresponds to total summation of fund holdings separated by asset classes. The portfolio holdings are divided into 3 assets; fixed income assets, domestic shares and foreign assets. Panel A lists the correlation of these 3 assets. Panel B shows the correlations among fixed income securities divided in 5 asset groups.

Table 3.4–Panel A. Correlation of Three Asset Classes, All Funds

PFA	Benchmark* Fixed Income Assets	Benchmark* Domestic Shares	Benchmark* Foreign Assets
Aporta	0.95	0.97	0.63
Bansander	0.93	0.97	0.90
Cuprum	0.98	0.99	0.85
Fomenta	0.97	0.97	0.56
Habitat	0.99	1.00	0.94
Magister	0.95	0.97	0.85
Planvital	1.00	1.00	0.92
Proteccion	1.00	1.00	0.88
Provida	0.99	1.00	0.95
Qualitas	0.96	0.97	---
SantaMaria	1.00	1.00	0.98
Summa	0.97	0.99	0.85
Union	0.99	0.98	0.78

*Summation of total assets of the industry decomposed into three asset classes.

Table 3.4–Panel B. Correlation in Weights of Fixed Income Securities, All Funds

PFA	Benchmark* Banking Bonds	Benchmark* Corporate Bonds	Benchmark* Certificates Deposits	Benchmark* Government Bonds	Benchmark* Mortgage-Backed Sec.
Aporta	0.71	-0.46	0.94	-0.56	0.16
Bansander	0.84	-0.51	0.63	0.62	0.44
Cuprum	0.29	0.99	-0.64	0.94	0.04
Fomenta	-0.14	-0.06	0.85	0.36	0.06
Habitat	-0.43	0.99	0.91	0.27	-0.24
Magister	0.90	1.00	0.80	0.91	0.43
Planvital	0.52	0.98	0.95	-0.49	0.40
Proteccion	0.89	0.66	0.88	0.75	0.23
Provida	0.76	1.00	0.87	0.65	0.47
Qualitas	-0.34	0.71	0.78	0.21	-0.21
SantaMaria	0.90	0.99	0.97	0.60	0.24
Summa	0.87	0.99	0.85	-0.36	0.50
Union	0.52	0.97	0.86	0.95	0.41

*Summation of total assets of the industry decomposed into three asset classes.

Table 3.4–Panel C. Correlation Matrix of Stock Weights (1997:06–1998:05)

	Aporta	Bansander	Cuprum	Fomenta	Habitat	Magister	Planvital	Proteccion	Provida	Qualitas	SantaMaria	Summa	Union
Aporta	1.00												
Bansander	0.99	1.00											
Cuprum	0.94	0.93	1.00										
Fomenta	0.93	0.92	0.98	1.00									
Habitat	0.96	0.96	0.99	0.97	1.00								
Magister	0.99	0.99	0.94	0.93	0.96	1.00							
Planvital	0.97	0.97	0.99	0.97	1.00	0.97	1.00						
Proteccion	0.98	0.97	0.98	0.97	1.00	0.98	1.00	1.00					
Provida	0.96	0.95	0.99	0.97	1.00	0.96	1.00	0.99	1.00				
Qualitas	0.98	0.98	0.93	0.92	0.97	0.99	0.97	0.97	0.96	1.00			
SantaMaria	0.98	0.97	0.99	0.97	0.99	0.98	1.00	1.00	0.99	0.97	1.00		
Summa	0.98	0.99	0.97	0.95	0.98	0.99	0.99	0.99	0.98	0.97	0.99	1.00	
Union	0.94	0.94	0.98	0.96	0.97	0.96	0.98	0.97	0.98	0.94	0.98	0.98	1.00

Table 3.4–Panel D. Correlation Matrix of Changes in Stock Weights (1997:06–1998:05)

	Aporta	Bansander	Cuprum	Fomenta	Habitat	Magister	Planvital	Proteccion	Provida	Qualitas	SantaMaria	Summa	Union
Aporta	1.00												
Bansander	0.93	1.00											
Cuprum	0.70	0.69	1.00										
Fomenta	0.67	0.71	0.74	1.00									
Habitat	0.76	0.81	0.93	0.70	1.00								
Magister	0.81	0.89	0.55	0.67	0.70	1.00							
Planvital	0.75	0.82	0.89	0.68	0.97	0.71	1.00						
Proteccion	0.83	0.87	0.91	0.68	0.97	0.72	0.98	1.00					
Provida	0.68	0.71	0.94	0.62	0.97	0.66	0.94	0.92	1.00				
Qualitas	0.75	0.74	0.53	0.43	0.67	0.89	0.64	0.66	0.70	1.00			
SantaMaria	0.79	0.85	0.92	0.72	0.97	0.75	0.93	0.96	0.94	0.68	1.00		
Summa	0.79	0.89	0.84	0.65	0.94	0.77	0.97	0.97	0.90	0.66	0.94	1.00	
Union	0.51	0.60	0.84	0.65	0.80	0.61	0.84	0.81	0.86	0.52	0.83	0.82	1.00

Table 3.4–Panel E. Correlation Matrix of Bond Weights (1997:06–1998:05)

	Aporta	Bansander	Cuprum	Fomenta	Habitat	Magister	Planvital	Proteccion	Provida	Qualitas	SantaMaria	Summa	Union
Aporta	1.00												
Bansander	0.13	1.00											
Cuprum	0.28	0.43	1.00										
Fomenta	0.40	0.02	0.68	1.00									
Habitat	-0.05	0.31	-0.29	-0.66	1.00								
Magister	0.09	0.51	0.80	0.70	-0.31	1.00							
Planvital	-0.18	-0.25	-0.69	-0.12	0.02	-0.27	1.00						
Proteccion	-0.13	0.35	0.77	0.49	-0.10	0.78	-0.36	1.00					
Provida	-0.20	-0.18	0.02	0.44	-0.58	0.39	0.41	0.19	1.00				
Qualitas	-0.21	0.01	0.63	0.42	-0.55	0.58	-0.49	0.69	0.44	1.00			
SantaMaria	0.60	0.71	0.39	0.19	0.26	0.41	-0.26	0.07	-0.36	-0.26	1.00		
Summa	-0.50	-0.24	-0.55	-0.13	0.04	-0.08	0.88	-0.01	0.57	-0.14	-0.48	1.00	
Union	0.16	0.54	0.93	0.71	-0.28	0.89	-0.44	0.80	0.27	0.58	0.35	-0.26	1.00

Table 3.4–Panel F. Correlation Matrix of Changes in Bond Weights (1997:06–1998:05)

	Aporta	Bansander	Cuprum	Fomenta	Habitat	Magister	Planvital	Proteccion	Provida	Qualitas	SantaMaria	Summa	Union
Aporta	1.00												
Bansander	-0.04	1.00											
Cuprum	0.42	0.49	1.00										
Fomenta	0.44	0.02	0.61	1.00									
Habitat	0.26	0.12	0.28	-0.25	1.00								
Magister	0.09	0.38	0.87	0.56	0.01	1.00							
Planvital	0.28	0.28	0.46	0.64	-0.11	0.35	1.00						
Proteccion	0.40	0.25	0.66	0.39	0.47	0.60	0.46	1.00					
Provida	0.07	-0.06	0.22	0.39	-0.42	0.49	0.21	0.03	1.00				
Qualitas	-0.07	-0.30	-0.28	-0.13	-0.54	0.03	-0.29	-0.12	0.54	1.00			
SantaMaria	0.33	0.54	0.84	0.34	0.31	0.74	0.25	0.57	0.05	-0.27	1.00		
Summa	0.10	0.13	0.49	0.46	0.14	0.52	0.80	0.66	0.37	-0.08	0.20	1.00	
Union	0.17	0.59	0.84	0.51	0.19	0.76	0.61	0.44	0.44	-0.31	0.64	0.65	1.00

Table 3.4–Panel G. Correlation Matrix of Changes in Stock Weights (1997:06–2001:12)

(7 PFAs and 54 monthly observations)

	Cuprum	Habitat	Magister	Planvital	Provida	SantaMaria	Summa
Cuprum	1.00						
Habitat	0.94	1.00					
Magister	0.70	0.67	1.00				
Planvital	0.91	0.97	0.68	1.00			
Provida	0.92	0.97	0.64	0.97	1.00		
SantaMaria	0.94	0.98	0.73	0.96	0.96	1.00	
Summa	0.82	0.88	0.60	0.87	0.83	0.85	1.00

Table 3.4–Panel H. Correlation Matrix of Changes in Bond Weights (1997:06–2001:12)

(7 PFAs and 54 monthly observations)

Change in	Cuprum	Habitat	Magister	Planvital	Provida	SantaMaria	Summa
Cuprum	1.00						
Habitat	0.07	1.00					
Magister	0.08	0.31	1.00				
Planvital	0.10	0.45	0.48	1.00			
Provida	0.18	0.14	0.23	0.20	1.00		
SantaMaria	0.14	0.55	0.42	0.49	0.25	1.00	
Summa	0.24	0.37	0.18	0.53	0.16	0.45	1.00

Table 3.5. Granger Causality Test on Changes in Stock Weights

The autoregressive expression $Y_t = \alpha_0 + \alpha_1 Y_{t-1} + ...\alpha_p Y_{t-p} + \beta_1 X_{t-1} + ...\beta_p X_{t-p} + \varepsilon_t$ is used to appraise whether *X Granger-causes Y* (Hamilton 1994). The null hypothesis is the βeta coefficients of the regressors X are equal to zero, i.e. $H_0 : \beta_1 = \beta_2 = ...\beta_p = 0$, *X does not Granger–cause Y*. The rejection decision of the null is based on the F-test at 1 percent. In the table, the dependent variable is listed in one column, and in three different columns, three possible independent variables are listed, which may be considered as X Granger-cause. The independent variables under consideration are *weighted average* of changes in stock loads, the *three leaders*, and finally either *one main fund or one pair of funds.* The selection of the third variable obeys the highest F-observed value between each fund, pairs of funds, and group of funds with respect to the dependent variable. In addition, in the last row of each subgroup of funds, the expression *Y Granger-cause X* is added to show the causality effect on the variables. The sample is divided into two sections: the acquired PFAs and the PFAs currently in the market. For instance, in the case of PFA Union, the first two rows are the possible independent variable (*X Granger-cause Y*) and third one, with an asterisk, refers to the interchange of variables (*Y Granger-cause X*) to prove one-way causality. Panel A arranges the pension funds in chronological order according to date of acquisition, with the earliest being first. The date in front of the dependent variable corresponds to the most significant relationship or the highest observed F-test to explain Granger causality. Panel B organizes the current pension funds according to size, with the largest funds first. The first three funds comprise the *leader* variable. *Weighted* is the weighted average of changes in stock weight in the PFA system. *Other* is the variable indicative of Granger causality among individual or pairs of funds.

Table 3.5–Panel A. Causality—Acquired Pension Funds

(Order based on the acquisition date)

Dependent Variable	Date of Acquisition[a]	Granger-cause[b] *Weighted*	Granger-cause[b] *Three Leaders*	Granger-cause[b] *Other*	Lags	F-Observed	Statistical Significance
1. Union	1998:05	Weighted	---	---	1	68.75	0.0%
Union		---	Leaders	---	1	58.00	0.0%
Weighted*		---	---	Union	1	1.06	30.7%
2. Bansander	1998:07	Weighted	---	---	1	42.28	0.0%
Bansander		---	Leaders	---	1	43.36	0.0%
Bansander		---	---	Cuprum [c]	1	67.13	0.0%
Weighted*		---	---	Bansander	1	1.41	24.0%
Cuprum*		---	---	Bansander	1	0.30	58.4%
3. Qualitas	1998:08	Weighted	---	---	1	37.79	0.0%
Qualitas		---	Leaders	---	1	37.50	0.0%
Weighted*		---	---	Qualitas	1	0.99	32.4%
Leaders*		---	---	Qualitas	1	0.85	36.1%
4. Fomenta		Weighted	---	---	1	33.21	0.0%
Fomenta		---	Leaders	---	1	28.54	0.0%
Fomenta	1998:09	---	---	Magister	1	80.83	0.0%
Magister*		---	---	Fomenta	1	0.42	52.1%
5. Proteccion		Weighted	---	---	1	26.65	0.0%
Proteccion	1998:12	---	Leaders	---	1	22.98	0.0%
Leaders*		---	---	Proteccion	1	1.65	20.4%
6. Aporta		Weighted	---	---	2	4.68	1.4%
Aporta		---	Leaders	---	2	3.93	2.6%
Aporta	2001:01	---	---	Cuprum [c]	2	5.30	0.8%
Cuprum*		---	---	Aporta	2	1.24	29.8%

(a) The date appears in the row with the most relevant variable to explain Granger causality.
(b) Independent variables.
(c) One of the three leaders.
* Here the independent and dependent variables are rotated to demonstrate causality in one direction.

Table 3.5–Panel B. Causality—Survivor Funds

(Arranged by asset values from the largest fund to the smallest)

Dependent Variable	Condition	Granger-cause* *Weighted*	Granger-cause* *Three Leaders*	Granger-cause* *Other*	Lags	F-Observed	Statistical Significance
1. Provida	Present	Weighted	---	---	6	4.12	0.20%
Provida		---	---	Cuprum	7	2.14	6.20%
Provida		---	---	Habitat	7	1.13	36.70%
Provida		---	---	Cuprum	8	4.57	0.10%
2. Habitat		Weighted	---	---	7	2.87	1.60%
Habitat	Present	---	---	Cuprum	7	3.36	0.70%
Habitat		---	---	Cuprum+Provida	7	2.59	2.60%
Habitat		---	---	Provida	7	1.08	39.70%
Habitat		---	---	Cuprum	6	2.04	8.20%
Habitat		---	---	Cuprum+Provida[¤]	6	1	44.10%
3. Cuprum		Weighted	---	---	6	2.18	6.40%
Cuprum		---	---	Habitat+Provida[¤]	6	3.22	1.10%
Cuprum		---	---	Provida	6	3.07	1.40%
Cuprum		---	---	Habitat	6	2.58	3.20%
Cuprum	Present	---	---	Habitat+Provida[¤]	7	4.22	0.10%
Cuprum		---	---	Habitat	7	4.9	0.00%
Cuprum		---	---	Provida	7	3.01	1.20%
4. SantaMaria		Weighted	---	---	5	2.03	9.30%
SantaMaria		---	---	Cuprum	5	2.58	3.90%
SantaMaria	Present	---	---	Habitat	5	3.45	1.00%
SantaMaria		---	---	Provida	5	1.46	22.10%
SantaMaria		---	---	Cuprum+Habitat[¤]	5	3.47	1.00%
Cuprum+Habitat		---	---	SantaMaria	5	2.48	4.60%

Table 3.5–Panel B, continued.

Dependent Variable	Condition	Granger-cause* *Weighted*	Granger-cause* *Three Leaders*	Granger-cause* *Other*	Lags	F-Observed	Statistical Significance
5. Summa		Weighted	---	---		2.03	9.30%
Summa	Present	---	---	Cuprum	5	3.67	0.70%
Summa		---	---	Habitat	5	1.53	20.10%
Summa		---	---	Provida	5	1.49	21.30%
Summa		---	---	Cuprum+Habitat¤	5	3.29	1.30%
Cuprum		---	---	Summa	5	1.47	21.80%
6. Magister		Weighted	---	---	7	1.99	8.00%
Magister		---	Leaders	---	7	1.79	11.60%
Magister	Present	---	---	Cuprum	7	2.6	2.60%
Magister		---	---	Habitat	7	1.56	17.60%
Magister		---	---	Provida	7	1.81	11.20%
7. Planvital		Weighted	---	---	6	3.24	1.00%
Planvital		---	Leaders	---	6	2.44	4.10%
Planvital	Present	---	---	Habitat+Provida¤	6	4.06	0.30%
Habitat+Provida		---	---	Planvital	6	3.15	4.10%

*Independent variables.

¤Formed with a simple average between two larger funds.

Table 3.6. Herding Level in the Chilean Pension Funds System

I report the herding values for pension funds using the methodology defined by Lakonishok *et al.* (1992). The number of pension funds diminished from thirteen to seven. By January 2001, there existed only seven pension funds as a consequence of assorted acquisitions. The herding measurement, applied to a given stock month (*i,t*) for the period 1997:06–2001:12, is equal to $H(i,t) = |p(i,t) - \overline{p}(t)| - AF(i,t)$ wherein *p(i,t)* is the proportion of traders who buy a given stock (*i*) at month (*t*). $\overline{p}(t)$ refers to the proportion of traders in month (*t*) who are buyers of all stocks (*i*). The adjustment factor, *AF(i,t)* is computed from the binomial distribution to allow the random variation of *p(i,t)* under the null hypothesis of no herding. The herding value is calculated each month (*t*) for all stocks (*i*) and averaged as a group according to number of traders (*N*). Panel A documents the herding value for both overall and each number of funds trading in the market. To show the effect of how the herding value changes as the number of traders increases, Panel B clusters the sample for trading funds from more than two to more than twelve. Finally, with a different categorization of the results, Panel C exhibits the mean values grouped by ranges of number of traders, and once more.

Table 3.6–Panel A. Herding Under Different Number of Traders

Number of Traders	Herding Mean	T-test
Overall (N³2)	1.8	5.40 ***
N=3	1.3	1.71 **
N=4	1.2	1.55 *
N=5	2.8	3.11 ***
N=6	5.4	4.76 ***
N=7	4.8	4.10 ***
N=8	7.0	3.86 ***
N=9	5.9	1.50 *
N=10	2.7	0.61
N=11	14.4	2.07 **
N=12	14.0	Ń ¤
N=13	34.5	9.86 ***

*Significant at 10 percent.
**Significant at 5 percent.
***Significant at 1 percent.
¤ Only one observation.

Table 3.6–Panel B. Herding as Number of Traders Increases

Number of Traders	Herding Mean***	T-test	Observations
N>2	2.7	6.84	1,417
N>3	3.5	7.44	923
N>4	4.7	8.20	600
N>5	5.9	7.93	376
N>6	6.2	6.35	218
N>7	7.4	4.91	116
N>8	8.2	3.00	39
N>9	10.2	2.66	21
N>10	18.4	3.35	10
N>11	27.7	3.88	3
N>12	34.5	9.86	2

***All mean values are significant at 1 percent.

Table 3.6–Panel C. Herding in Certain Ranges of Number of Funds Trading

Number of Traders	Herding Mean***	T-test	Observations
2<N<7	2.1	4.84	1,199
3<N<8	2.9	6.00	807
4<N<9	4.5	7.66	561
5<N<10	5.6	7.49	355
6<N<11	5.6	5.77	208
7<N<12	6.8	4.55	113

***All mean values are significant at 1 percent.

Table 3.7. Herding Level Using the Sias (2004) Approach

I report the result of herding measure using Sias (2004) approach. I consider the cases that PFA (i) trades at least in 2 periods consecutively. In some cases, this condition limits the analysis since sometimes PFA trades in consecutive period the stock (k). The regressions run are models (3.6) and (3.7) where model (3.6) is defined as: $\Delta_{k,t} = \beta_t \Delta_{k,t-1} + \varepsilon_{k,t}$ with $\Delta_{k,t} = \dfrac{Raw\Delta_{k,t} - \overline{Raw\Delta_t}}{\sigma(Raw\Delta_{k,t})}$ and

$$Raw\Delta_{k,t} = \frac{Buyers_{k,t}}{Buyers_{k,t} + Sellers_{k,t}} \qquad k = stock$$

Additionally, model (3.6) is decomposed into model (3.7):

(7) $\beta_{k,t} = \rho(\Delta_{k,t}, \Delta_{k,t-1}) =$

$$\left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] * \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{n,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right] +$$

$$\left[\frac{1}{(K-1)\sigma(Raw\Delta_{k,t})\sigma(Raw\Delta_{k,t-1})}\right] * \sum_{k=1}^{K}\left[\sum_{n=1}^{N_{k,t}} \sum_{m=1,m\neq n}^{N_{k,t-1}} \frac{(D_{n,k,t} - \overline{Raw\Delta_t})(D_{m,k,t-1} - \overline{Raw\Delta_{t-1}})}{N_{k,t}N_{k,t-1}}\right]$$

	Beta Coefficient	Average R^2	Own Trades	Others Trades
N>0	0.344	0.160	0.031	0.313
	(11.82)		(12.44)	(9.62)
N>1	0.262	0.149	0.045	0.218
	(6.28)		(7.88)	(5.73)
N>2	0.571	0.020	0.068	0.502
	(4.92)		(4.62)	(3.67)
N>3	0.786	0.110	0.181	0.605
	(4.59)		(3.58)	(4.37)
Quintile 1	0.338	0.180	0.041	0.298
	(6.92)		(6.27)	(7.45)
Quintile 5	0.185	0.082	0.030	0.156
	(1.80)		(3.95)	(1.51)

Table 3.8. Herding Values of Chilean Pension Funds for Different Periods

I report the herding values for pension funds using the methodology defined by Lakonishok *et al.* (1992). The number of pension funds diminished from thirteen to seven. By January 2001, there existed only seven pension funds as a consequence of assorted acquisitions. The herding measurement, applied to a given stock month (*i,t*) for the period 1997:06–2001:12, is equal to $H(i,t) = |p(i,t) - \overline{p}(t)| - AF(i,t)$ wherein *p(i,t)* is the proportion of traders who buy a given stock (*i*) at month (*t*). $\overline{p}(t)$ refers to proportion of traders in month (*t*) who are buyers of all stocks (*i*). The adjustment factor, *AF(i,t)* is computed from the binomial distribution to allow the random variation of *p(i,t)* under the null hypothesis of no herding. The herding value is calculated each month (*t*) for all stocks (*i*) and averaged as a group according to number of traders (*N*). Panel A shows evidence of the effect of the two financial crises on the herding mean applied to two different groups of traders (N>1 and N>5). In the case of the Asian crisis, two categories of dates are evaluated, the whole crisis duration and the date of the greatest fall of Chilean Stock Exchange (1998:01) during this crisis. The Russian crisis effect on the stock market is appraised for its duration (one month). Panel B reports the effect of the change in legislation of an extension in the length of the measure period of the MGR. The former procedure applied was to consider the past-12-months average return, while the new methodology uses the past-36-months average return. The base period is 1998:09–1999:10 and the following ones correspond to how the pension funds reacted to this amendment. The period 1997:06–1998:07 is presented to illustrate the whole sample.

Table 3.8–Panel A. Effect of Financial Crises on Herding Activity

Event	Date	Traders	$\bar{p}(t)$	Herding Mean (%)	T-Test
Asian Crisis	1997:06-1998:01	N>1	0.38	3.71	4.80 ***
	1998:01:00	N>1	0.23	3.46	1.97 **
	1997:06-1998:01	N>5	0.38	7.43	4.85 ***
	1998:01:00	N>5	0.23	4.93	1.73 **
Russian Crisis	1998:08:00	N>1	0.33	-0.01	-0.43
	1998:08:00	N>5	0.33	0.00	0.21

***Statistically significant at 1%.

**Statistically significant at 5%.

Table 3.8–Panel B. Effect of the Appraisal Period Enlargement of Minimum Return

(From the past 12 months to the past 36 months, as of October 1999)

Period	Traders	Observations	Herding Value (%)	T-Test
1997:06-1998:07	N>1	697	3.25	5.61 ***
1998:09-1999:10	N>1	375	0.37	0.46
1999:11-2000:11	N>1	475	1.47	2.21 **
2000:12-2001:12	N>1	426	1.58	1.79 **
1997:06-1998:07	N>2	491	4.16	6.06 ***
1998:09-1999:10	N>2	243	1.81	1.90 **
1999:11-2000:11	N>2	344	0.92	1.27 *
2000:12-2001:12	N>2	276	3.37	3.31 ***
1997:06-1998:07	N>3	343	4.86	6.15 ***
1998:09-1999:10	N>3	146	2.54	2.04 **
1999:11-2000:11	N>3	233	1.96	2.40 **
2000:12-2001:12	N>3	152	4.02	3.09 ***

***Statistically significant at 1%.
**Statistically significant at 5%.
*Statistically significant at 10%.

Table 3.9. Herding in Market Capitalization Stocks

I report the herding values for pension funds using the methodology defined by Lakonishok *et al.* (1992). The number of pension funds diminished from thirteen to seven. By January 2001, there existed only seven pension funds as a consequence of assorted acquisitions. The herding measurement, applied to a given stock month (*i,t*) for the period 1997:06–2001:12, is equal to $H(i,t) = |p(i,t) - \overline{p}(t)| - AF(i,t)$ wherein *p(i,t)* is the proportion of traders who buy a given stock (*i*) at month (*t*). $\overline{p}(t)$ refers to proportion of traders in month (*t*) who are buyers of all stocks (*i*). The adjustment factor, *AF(i,t)* is computed from the binomial distribution to allow the random variation of *p(i,t)* under the null hypothesis of no herding. The herding value is calculated each month (*t*) for all stocks (*i*) and averaged as a group according to number of traders (*N*). Panel A exhibits herding values for each quintile under different number of traders in the market. Panel B and C list results for stocks of different economic sectors.

Table 3.9–Panel A. Herding by Quintiles—Market Size

Quintile	Number of Traders	Herding	Observations
Q1	N>1	2.89 ***	770
Q2	N>1	1.14 **	663
Q3	N>1	0.13	386
Q4	N>1	1.80 *	142
Q5	N>1	5.88 ***	97
Q1	N>3	4.14 ***	486
Q2	N>3	2.34 **	293
Q3	N>3	2.57 **	103
Q4	N>3	4.05 *	21
Q5	N>3	9.20 **	20

***Statistically significant at 1%.
**Statistically significant at 5%.
*Statistically significant at 10%.

Table 3.9–Panel B. Herding by Economic Sector

Industry	Herding Value (%) if N>1	Herding Value (%) if N>3
A. Power Plants	3.03 ***	4.31 ***
B. Energy Distribution	1.88 *	4.65 **
C. Telecommunication	4.47 ***	5.22 ***
D. Forestry	0.82	3.26 ***
E. Banks	1.43	2.94 **
F. Foods	3.44 ***	4.22 ***
G. Retailers	-0.17	0.89
H. Manufacturing	0.84	2.60 **

***Statistically significant at 1%.
**Statistically significant at 5%.
*Statistically significant at 10%.

Table 3.9–Panel C. Herding by Larger Stock Within Each Economic Sector

Individual Stock[¤]	Herding Value (%) if N>1	Herding Value (%) if N>3
A. Endesa	2.98 **	2.68 *
A. Chilgener	6.38 ***	6.33 ***
B. Enersis	6.42 ***	6.36 **
B. Chilectra	2.64	0
C. CTC	6.87 ***	6.96 ***
C. Entel	2.92 **	3.22 **
D. Copec	4.41 **	4.6 **
D. CMPC	1.88	2.1 *
E. Banco Chile	6	0
E. Banco Crˇdito	0.07	1.48
F. Cervezas	6.63 ***	9.18 ***
F. Andina	0.82	1.57
G. Falabella	2.16	1.04
G. DS	1.2	2.91
H. Cap	0.02	0.88
H. LabChile	3.55 **	6.27 ***

[¤] The capital letters A., B., . . . H. refer to the economic sectors indicated in Panel B.

***Statistically significant at 1%.

**Statistically significant at 5%.

*Statistically significant at 10%.

Table 3.10–Panel A. Censored Dependent Variable and Quintiles

Regressors [(1)]	Coefficients [(2)]	Probability of (0.0<Herd<0.05)	Probability of (0.05<Herd<0.1)	Probability of (0.1<Herd<0.2)
Constant	-0.03 (7.81)**			
Q1	0.0204 (3.81)**	0.175	0.115	0.124
Q3	-0.0026 -0.46	0.159	0.112	0.088
Q4	0.0111 -1.59	0.17	0.127	0.108
Q5	0.0081 -1.01	0.168	0.124	0.104

[(1)] Variable Dummy Base: *Q2* . Statistical Output: L.Ratio Chi-Squared(4) = 21.43. Significance Prob > chi2 = 0.0003. Standard Errors of Coefficients = 0.1041 (53.27) **. Absolute values of z-statistics in parenthesis.

[(2)] Below the regressor coefficient lies the T-test. In parentheses with **, significant at 1 percent.

Table 3.10–Panel B. Censored Dependent Variable and Number of Traders

Regressors [1]	Coefficients [2]	Probability of (0.0<Herd<0.05)	Probability of (0.05<Herd<0.1)	Probability of (0.1<Herd<0.2)
Constant	-0.0324 (9.30)**			
2≤Traders≤3	-0.0017 -0.35	0.160	0.110	0.084
4≤Traders≤5	0.019 (3.23)**	0.176	0.133	0.115
6≤Traders≤7	0.0548 (6.86)**	0.189	0.169	0.182
8≤Traders≤11	0.0552 (4.91)**	0.189	0.169	0.183

(1) Variable Dummy Base: Traders>11. Statistical Output: L.Ratio Chi-Squared(4) = 81.01. Significance Prob > chi2 = 0.000. Standard Errors of Coefficients = 0.1024 (53.25) **. Absolute values of z-statistics in parenthesis.

(2) Below the regressor coefficient lies the T-test. In parentheses with **, significant at 1 percent.

Table 3.10–Panel C. Censored Dependent Variable and Group of Stocks Size

Regressors [(1)]	Coefficients [(2)]	Probability of (0.0<Herd<0.05)	Probability of (0.05<Herd<0.1)	Probability of (0.1<Herd<0.2)
Constant	-0.0226 (3.80)**			
StockSize1_5	0.0369 (3.88)**	0.550	0.160	0.167
StockSize6_10	0.0055 -0.59	0.430	0.129	0.111
StockSize11_20	0.0043 -0.53	0.426	0.127	0.109
StockSize21_30	-0.006 -0.75	0.387	0.116	0.094
StockSize31_40	-0.0064 -0.79	0.386	0.116	0.093
StockSize41_80	-0.007 -1.01	0.384	0.115	0.092

(1) Variable Dummy Base: StockSize81_greater. Statistical Output: L.Ratio Chi-Squared(6) = 32.65. Significance Prob > chi2 = 0.000. Standard Errors of Coefficients = 0.1039 (53.28) **. Absolute values of z-statistics in parenthesis.

(2) Below the regressor coefficient lies the T-test. In parentheses with **, significant at 1 percent.

Table 3.10–Panel D. Censored Dependent Variable and Large Stocks of Quintiles

Regressors [1]	Coefficients [2]	Probability of (0.0<Herd<0.05)	Probability of (0.05<Herd<0.1)	Probability of (0.1<Herd<0.2)
Constant	-0.0264 (11.71)**			
Q1_CTC	0.0538 (3.29)**	0.152	0.171	0.194
Q1_Endesa	0.0451 (2.77)**	0.151	0.164	0.176
Q1_Enersis	0.0332 (2.04)*	0.148	0.153	0.153
Q1_Entel	0.0481 (2.93)**	0.152	0.167	0.182
Q1_Cervezas	0.037 (2.27)*	0.150	0.157	0.160
Q5_Maderas	0.0288 -0.74	0.147	0.149	0.145
Q5_Pilmaiquen	-0.0375 -1.47	0.102	0.079	0.051
Q5_Quemchi	0.0793 -0.94	0.149	0.186	0.246
Q5_Quilicura	-0.0057 -0.14	0.128	0.113	0.089
Q5_Somela	0.0463 -1.46	0.151	0.165	0.178

[1] Variable Dummy Base: Remaining_Stocks. Statistical Output: L.Ratio Chi-Squared(10) = 40.63. Significance Prob > chi2 = 0.000. Standard Errors of Coefficients = 0.1039 (53.29) **. Absolute values of z-statistics in parenthesis.

[2] Below the regressor coefficient lies the T-test. In parentheses with **, significant at 1 percent. In parentheses with *, significant at 5 percent.

Table 3.10–Panel D. Censored Dependent Variable and Large Stocks of Quintiles

Regressors [1]	Coefficients [2]	Probability of (0.0<Herd<0.05)	Probability of (0.05<Herd<0.1)	Probability of (0.1<Herd<0.2)
Constant	-0.0264 (11.71)**			
Q1_CTC	0.0538 (3.29)**	0.152	0.171	0.194
Q1_Endesa	0.0451 (2.77)**	0.151	0.164	0.176
Q1_Enersis	0.0332 (2.04)*	0.148	0.153	0.153
Q1_Entel	0.0481 (2.93)**	0.152	0.167	0.182
Q1_Cervezas	0.037 (2.27)*	0.150	0.157	0.160
Q5_Maderas	0.0288 -0.74	0.147	0.149	0.145
Q5_Pilmaiquen	-0.0375 -1.47	0.102	0.079	0.051
Q5_Quemchi	0.0793 -0.94	0.149	0.186	0.246
Q5_Quilicura	-0.0057 -0.14	0.128	0.113	0.089
Q5_Somela	0.0463 -1.46	0.151	0.165	0.178

[1] Variable Dummy Base: Remaining_Stocks. Statistical Output: L.Ratio Chi-Squared(10) = 40.63. Significance Prob > chi2 = 0.000. Standard Errors of Coefficients = 0.1039 (53.29) **. Absolute values of z-statistics in parenthesis.

[2] Below the regressor coefficient lies the T-test. In parentheses with **, significant at 1 percent. In parentheses with *, significant at 5 percent.

Table 4.1. Changes in Market Share after Mergers

Panels A and B exhibit information about the market share of each pension fund measured as a function of the total number of clients and total assets value. In the initial period, 1997:06–1998:05, there were thirteen pension funds. Between 1998:06 and 1998:07, the first two mergers occurred. The next two mergers occurred in 1998:08 and 1998:09, and the last two occurred in 1999:12 and 2001:01. In the last four columns of the Panels, I list the final market share of each fund after mergers. Due to rounding of numbers, the total summation of each column is not exactly equal to 1.0.

Table 4.1–Panel A. Market Share Based on Clients (in percentage)

(Sorted by size based on the period 1997:06-1998:05)

Funds	1997:06 - 1998:05	1998:08 - After two mergers	1998:10 - After four mergers	2001:02 - After six mergers	2001:12
PFA 9	19.4	23.3	23.5	31.8	31.8
PFA 5	18.6	20.9	21.5	22.5	22.8
PFA 3	17.5	16.8	16.8	16.1	16
PFA 11	12.4	12.5	12.5	12.7	12.9
PFA 8	9.5	9.1	8.9	---	---
PFA 12	7.5	11.8	11.4	11.2	11
PFA 2	5.1	---	---	---	---
PFA 13	4.2	---	---	---	---
PFA 7	2.6	2.6	2.5	2.7	2.8
PFA 6	1.3	1.2	1.6	3.1	2.8
PFA 1	0.8	0.6	1.3	---	---
PFA 10	0.6	0.5	---	---	---
PFA 4	0.5	0.6	---	---	---

Table 4.1–Panel B. Market Share Based on Asset Values (in percentage)

(Sorted by size based on the period 1997:06-1998:05)

Funds	1997:06 - 1998:05	1998:08 - After two mergers	1998:10 - After four mergers	2001:02 - After six mergers	2001:12
PFA 9	19.4	23.3	23.5	31.8	31.8
PFA 5	18.6	20.9	21.5	22.5	22.8
PFA 3	17.5	16.8	16.8	16.1	16
PFA 11	12.4	12.5	12.5	12.7	12.9
PFA 8	9.5	9.1	8.9	---	---
PFA 12	7.5	11.8	11.4	11.2	11
PFA 2	5.1	---	---	---	---
PFA 13	4.2	---	---	---	---
PFA 7	2.6	2.6	2.5	2.7	2.8
PFA 6	1.3	1.2	1.6	3.1	2.8
PFA 1	0.8	0.6	1.3	---	---
PFA 10	0.6	0.5	---	---	---
PFA 4	0.5	0.6	---	---	---

Table 4.2. Descriptive Statistics of Chilean Pension Funds

All the numbers are obtained from monthly Interim Financial Income Statements. As financial report values are accumulatively recorded, I determine the monthly variation between two months. The same procedure is applied when I study the information from December of year X1 to January of year X2. The monthly mean values are computed for each year on the basis of monthly variations within that year. For instance, Total Expenses/Total Revenues for 1997:06–1997:12 is calculated as a monthly mean variation of seven periods. ($) refers to pesos, the Chilean currency. Using the exact translation from the Pension Fund Act, I use “clients” to refer to pension fund clients.

Table 4.2–Panel A. Revenues—Monthly Mean Values

	1997:06 - 1997:12	1998:01 - 1998:12	1999:01 - 1999:12	2000:01 - 2000:12	2001:01 - 2001:12
Variable Fee (% on taxable salary)	3.00%	2.80%	2.70%	2.60%	2.50%
Fixed Fee ($)	216	334	455	547	581
Total Income per Client ($)	4,029	3,932	4,313	4,819	4,296
Net Operating Income per Client ($)	355	690	1,250	1,964	1,508

Table 4.2–Panel B. Expenses*—Monthly Mean Values

	1997:06 - 1997:12	1998:01 - 1998:12	1999:01 - 1999:12	2000:01 - 2000:12	2001:01 - 2001:12
Total Expenses / Total Revenues	0.824	0.811	0.694	0.641	0.61
Advertising Expenses / Total Expenses	0.043	0.019	0.018	0.014	0.018
Salesforce Expenses / Total Expenses	0.357	0.302	0.262	0.154	0.139
Advertising Expenses per Client ($)	145	72	61	40	55
Salesforce Expenses per Client ($)	1,305	1,016	739	426	365
Total Expenses per Clients ($)	3,674	3,242	3,063	2,855	2,788

*Total Expenses are composed of salespersonsÕ wages, disability insurance, administration, advertising, employeesÕ wages, board, and depreciation.

Table 4.2–Panel C. Assets—Monthly Total Mean Values

	1997:06 - 1997:12	1998:01 - 1998:12	1999:01 - 1999:12	2000:01 - 2000:12	2001:01 - 2001:12
Total Assets of Funds (Million Pesos)	13,500,000	13,900,000	16,900,000	19,600,000	22,100,000
Total Assets of Funds (Million Dollars)	32,300	30,200	33,200	36,400	35,000
Total Number of Clients	5,715,432	5,862,088	6,022,070	6,183,198	6,348,499
Total Number of Salespeople	19,366	9,914	4,265	3,270	2,673
Total Number of Workers*	24,473	14,713	8,479	6,974	6,188

*Including salespersons.

Table 4.3: Clusters of Pension Funds and Financial Ratios

(As of December of each year)

The information presented this table illustrates some financial ratios relative to expenses, revenues, and assets, calculated using the financial reports ending as of December of each year. The sample is divided into four categories: (i) Acquired funds (those absorbed by others), (ii) Survivors, (iii) the Three Leaders (based on asset values, not number of clients), and (iv) the Industry Value (which is computed using the total values of the market and not on either the simple or the weighted average of funds).

Table 4.3. Clusters of Pension Funds and Financial Ratios

(As of December of each year)

	Industry Value*	Merged Funds	Survivor Funds	Leader Funds
1997				
Revenues / Fund Assets	2.09	2.12	2.09	2.14
Fee Income / Fund Assets	1.95	2	1.94	2.02
Expenses / Fund Assets	1.77	2.77	1.85	1.61
Marketing Expenses / Fund Assets	0.7	1.06	0.7	0.64
Net Operating Income / Fund Assets	0.32	-0.65	0.24	0.53
1998				
Revenues / Fund Assets	1.88	1.62	1.88	1.91
Fee Income / Fund Assets	1.78	1.56	1.76	1.84
Expenses / Fund Assets	1.55	1.57	1.62	1.44
Marketing Expenses / Fund Assets	0.52	0.56	0.51	0.49
Net Operating Income / Fund Assets	0.33	0.06	0.26	0.47
1999				
Revenues / Fund Assets	1.7	1.58	1.7	1.68
Fee Income / Fund Assets	1.44	1.42	1.45	1.45
Expenses / Fund Assets	1.21	1.57	1.28	1.14
Marketing Expenses / Fund Assets	0.32	0.39	0.35	0.3
Net Operating Income / Fund Assets	0.49	0.01	0.42	0.54
2000				
Revenues / Fund Assets	1.74	1.54	1.8	1.46
Fee Income / Fund Assets	1.32	1.45	1.37	1.31
Expenses / Fund Assets	1.03	1.43	1.12	0.94
Marketing Expenses / Fund Assets	0.17	0.33	0.21	0.14
Net Operating Income / Fund Assets	0.71	0.11	0.68	0.53
2001				
Revenues / Fund Assets	1.41	---	1.41	1.41
Fee Income / Fund Assets	1.22	---	1.25	1.22
Expenses / Fund Assets	0.92	---	1	0.85
Marketing Expenses / Fund Assets	0.14	---	0.17	0.12
Net Operating Income / Fund Assets	0.5	---	0.41	0.56

*Computed on total market values.

Table 4.4: Monthly Fund Flow Variations

(Measured by the assets value and the number of clients)

The net flows of each pension fund are measured by *Flows_Pesos* and *Flow_Clients*. *Flows_Pesos* corresponds to the percentage variation of asset values, computed on local currency, between two periods, and is given by Model (4.1) [86]. To better understand the major source the variation in flows, Model (1) is widened into Model (4.2), and later divided into: *Quantity_Flow* (4.2a) and *Value_Flow* (4.2b) which tend to account for changes in flows due to variation in both the number of clients and the saving accounts size. In Model (4.3), *Flow_Clients* is defined as the percentage variation in the number of clients adjusted by the number of clients added to fund (*i*) from fund (*j*) due to mergers. Panel A illustrates the monthly average value of Models (4.2), (4.2a), (4.2b), and (4.3) for the period 1997:06–1998:05. In that period, there were thirteen pension funds. Panel B presents the same as the prior models, but for the period 1998:10–2001:01, after four mergers took place. Panel C does the same as Panel B, but for the period after 2001:01.

(4.1) $$Flow\_Pesos_{i,t} = \frac{Asset_{i,t} - Asset_{i,t-1} * (1 + Return_{i,t}) - Merger_{i,t}}{Asset_{i,t-1}}$$

(4.2) $$Flow\_Pesos_{i,t1} = \frac{\left(\frac{Asset_{i,t1} - Merger_{i,t1}}{Clients_{i,t1}}\right) * Clients_{i,t1} - \left(\frac{Asset_{i,t0} * (1 + Return_{i,t1})}{Clients_{i,t0}}\right) * Clients_{i,t0}}{Asset_{i,t0}}$$

(4.2a) $$Quantity\_Flow_{i,t1} = \frac{\left(Asset_{i,t1} - Merger_{i,t1}\right)}{Clients_{i,t1}} * \left(Clients_{i,t1} - Clients_{i,t0}\right) * \frac{1}{Asset_{i,t0}}$$

86 Fund flows have been extensively used in the U.S. mutual fund literature, as in Zheng (1999), Sirri and Tufano (1998), Carhart (1997), and Gruber (1996). I use the definition of Huang, Wei, and Yan (2003). Unlike these papers, my study decomposes *Flow_pesos* into two components, *Value* and *Quantity*.

(4.2b) $$Value\_Flow = Clients_{i,t0} * \left[\left(\frac{Asset_{i,t1} - Mergers_{i,t1}}{Clients_{i,t1}} \right) - \left(\frac{Asset_{i,t0} * (1 + Return_{i,t1})}{Clients_{i,t0}} \right) \right] * \frac{1}{Asset_{i,t0}}$$

(4.3) $$Flow\_Clients_{i,t} = \frac{Clients_{i,t} - Clients_{i,t-1} - Client.Merger_{i,t}}{Clients_{i,t-1}}$$

Table 4.4–Panel A. Fund Flow Variations—Period 1997:06–1998:05

(Before any mergers - monthly average percentage change)

	Flow_Pesos (%)*	*Quantity_Flow* (%)	*Value_Flow* (%)	*Flow_Clients* (%)
PFA 1[a]	-0.86	-0.72	-0.14	-0.73
PFA 2[a]	-0.64	0.71	-1.35	0.72
PFA 3	0.06	0.77	-0.71	0.78
PFA 4[a]	0.67	1.44	-0.77	1.47
PFA 5	1.45	0.67	0.78	0.67
PFA 6	-0.13	-0.13	0.00	-0.13
PFA 7	0.34	-0.44	0.77	-0.44
PFA 8[a]	0.55	1.02	-0.47	1.03
PFA 9	0.19	0.26	-0.07	0.26
PFA 10[a]	-1.49	-1.30	-0.19	-1.32
PFA 11	0.52	0.10	0.42	0.10
PFA 12	0.08	0.22	-0.14	0.22
PFA 13[a]	-0.71	-0.62	-0.09	-0.63
System	0.37	0.30	0.07	0.30

*Flow_Pesos = Quantity Flow + Value Flow. Summation not exact due to rounding numbers for presentation.

[a]PFAs that merged and disappeared through time.

Table 4.4–Panel B. Fund Flow Variations—Period 1998:10–2001:01

(After four mergers - monthly average percentage change)

	Flow_Pesos (%)*	*Quantity_Flow* (%)	*Value_Flow* (%)	*Flow_Clients* (%)
PFA1[a]	0.14	0.17	-0.03	0.17
PFA2[ab]	---	---	---	---
PFA3	0.12	0.10	0.02	0.10
PFA4[ab]	---	---	---	---
PFA5	0.44	0.39	0.05	0.38
PFA6	1.09	0.35	0.74	0.34
PFA7	0.57	-0.09	0.66	-0.08
PFA8[a]	0.30	0.01	0.29	0.30
PFA9	0.26	0.30	-0.04	0.68
PFA10[ab]	---	---	---	---
PFA11	0.34	0.15	0.20	0.15
PFA12	0.22	0.17	0.05	0.17
PFA13[ab]	---	---	---	---
System	0.29	0.25	0.04	0.24

*Flow_Pesos = Quantity Flow + Value Flow. Summation not exact due to rounding numbers for presentation.

[a]PFAs that merged and disappeared through time.

[b]PFA 2 and PFA 13 merged with PFA 11 and PFA 9, respectively. PFA 4 and PFA 10 merged with PFA 1 and PFA 16, respectively.

Table 4.4–Panel C. Fund Flow Variations—Period 2001:02–2001:12

(After all mergers - monthly average percentage change)

	Flow_Pesos (%)*	*Quantity_Flow* (%)	*Value_Flow* (%)	*Flow_Clients* (%)
PFA1[ac]	---	---	---	---
PFA2[ab]	---	---	---	---
PFA3	0.24	0.10	0.14	0.10
PFA4[ab]	---	---	---	---
PFA5	0.38	0.34	0.04	0.34
PFA6	-1.11	-0.76	-0.36	-0.76
PFA7	0.41	0.03	0.38	0.03
PFA8[ac]	---	---	---	---
PFA9	0.28	0.28	0.00	0.28
PFA10[ab]	---	---	---	---
PFA11	0.35	0.06	0.30	0.06
PFA12	0.09	0.05	0.04	0.05
PFA13[ab]	---	---	---	---
System	0.25	0.20	0.05	0.20

*Flow_Pesos = Quantity Flow + Value Flow. Summation not exact due to rounding numbers for presentation.

[a]PFAs that merged and disappeared through time.

[b]Before 1998:09, PFA 2 and PFA 13 merged with PFA 11 and PFA 9, respectively, and PFA 4 and PFA 10 merged with PFA 1 and PFA 6, respectively.

[c]Between 1998:09 and 2001:01, PFA 1 and PFA 8 merged with PFA 6 and PFA 9, respectively.

Table 4.5. Relationship between Flow and Past Performance

This table reports the coefficient values of regression models applied to flow definitions, *Flow_Pesos*$_{i,t}$ and *Flow_Clients*$_{i,t}$. The dependent variable *Flow_Pesos*$_{i,t}$ is divided into (i) *Quantity_Flow* and (ii) *Value_Flow*.

I use models (4.4) and (4.5) to investigate whether fund flows react to past performance measured within different periods of time. As control variables, the model uses a one-lag logarithm of Assets Value (*LOG(Asset)*$_{i,t-1}$) and standard deviation of 3-month returns (*Standard.Deviation*$_{i,t}$). Variable fees and Fixed fees are included with one-lag period (*VarFee*$_{i,t-1}$, *FixFee*$_{i,t-1}$). Performance (*Premium*) is measured as excess return on the benchmark (weighted average return) defined specifically in the Pension Funds Act. This is computed for three different revolving periods (*T*): 1-month, 6-months, and 12-months, and it is lagged 3-months. *Premium_12month*$_{i,t-3}$ denotes the rolling past-12-months excess return lagged 3 months. Additionally, as robustness, *raw return*$_{i,t-3}$ is used as alternative independent variable to performance. These models are regressed under three additional specifications. Models A, B and C are estimated using the methodology of Fama-Macbeth (1973) with cross-sectional regressions on monthly fund flows for the periods $T=1$, $T=6$ and $T=12$ months, respectively. The results are exhibited in Panels A and C. Panels B and D present results of the above models under fixed-effect model as an alternative procedure to test the robustness of findings.

The absolute values of t-statistics are shown in brackets under each coefficient. Asterisks (*, **, and ***) indicate the significance level of coefficients at 10%, 5%, and 1%, respectively. Listed at the bottom of each panel are the number of observations, number of units (*i*), R-squared values, F-test, and Hausman specification test (H_0: *Correlation Coeff.*$(u_i , X)=0$) for each fixed-effect model.

$$(4.4)\quad Flow\_Pesos_{i,t} = \alpha + \beta_1 LOG(Asset)_{i,t\text{-}1} + \beta_2 Standard.Deviation_{i,t} + \beta_3 FixFees_{i,t\text{-}1} + \beta_4 VarFees_{i,t\text{-}1} + \beta_5 Premium\_Tmonth_{i,t\text{-}3} + \varepsilon_{i,t} \qquad T = 1, 6, 12$$

$$(4.5)\quad Flow\_Clients_{i,t} = \alpha + \beta_1 LOG(Asset)_{i,t\text{-}1} + \beta_2 Standard.Deviation_{i,t} + \beta_3 FixFees_{i,t\text{-}1} + \beta_4 VarFees_{i,t\text{-}1} + \beta_5 Premium\_Tmonth_{i,t\text{-}3} + \varepsilon_{i,t} \qquad T = 1, 6, 12$$

Table 4.5–Panel A1. Dependent variable is *Flow_Pesos* under Fama-Macbeth (1973)

Regressors	Model 4.4A Prem_1m	Model 4.4B Prem_6m	Model 4.4C Prem_12m
Intercept	0.208	0.117	0.26
	[1.16]	[1.32]	[2.35]**
Lag LOG(Asset)	-0.008	-0.004	-0.009
	[1.09]	[1.20]	[2.17]**
Standard.Deviation	0.01	-0.003	-0.014
	[0.73]	[0.38]	[1.41]
LagVarFee	-4.01	-1.87	-4.01
	[1.22]	[1.28]	[2.21]**
LagFixFee	-0.005	-0.002	-0.016
	[0.42]	[0.29]	[1.83]*
Lag3 Prem_1m	-0.854	---	---
	[0.57]		
Lag3 Prem_6m	---	-0.067	---
		[0.18]	
Lag3 Prem_12m	---	---	0.38
			[2.31]**
Cross Section Regressions	54	49	43
Number of Funds	13	13	11

Table 4.5–Panel A2. Dependent Variable is *Flow_Clients* under Fama-Macbeth (1973)

Regressors	Model 4.5A Prem_1m	Model 4.5B Prem_6m	Model 4.5C Prem_12m
Intercept	-0.01 [0.20]	0.051 [0.39]	0.079 [1.42]
Lag LOG(Asset)	0.001 [0.43]	-0.001 [0.50]	-0.002 [0.29]
Standard.Deviation	0.013 [0.06]	0.004 [0.49]	-0.005 [0.35]
LagVarFee	-0.468 [0.63]	-1.22 [0.25]	-1.538 [0.12]
LagFixFee	0.002 [0.63]	-0.003 [0.44]	-0.005 [0.18]
Lag3 Prem_1m	-0.475 [0.51]	---	---
Lag3 Prem_6m	---	-0.399 [0.26]	---
Lag3 Prem_12m	---	---	0.029 [0.77]
Cross Section Regressions	54	49	43
Number of Funds	13	13	11

Table 4.5–Panel B1. Dependent Variable is *Flow_Pesos* under Fixed Effect

Regressors	Model 4.4A Prem_1m	Model 4.4B Prem_6m	Model 4.4C Prem_12m
Intercept	---	---	---
Lag LOG(Asset)	-0.002 [0.30]	-0.003 [1.30]	-0.013 [3.46]***
Standard.Deviation	-0.0006 [0.22]	-0.0009 [1.47]	-0.0011 [1.55]
LagVarFee	-0.919 [0.15]	-0.19 [0.23]	-3.83 [2.78]**
LagFixFee (000s)	-0.008 [0.10]	-0.002 [0.30]	-0.035 [2.61]**
Lag3 Prem_1m	-0.13 [0.69]	---	---
Lag3 Prem_6m	---	0.35 [2.60]**	---
Lag3 Prem_12m	---	---	0.48 [4.83]***
Observations	466	401	325
Number of Funds	13	13	11
F test: All coeff = 0	0.87	2.19	10.05
Prob. > F-test	0.50	0.05	0.00
Hausman Test Chi(^{2})	8.65	15.80	20.18
Prob.>Chi-Squared	0.00	0.00	0.00

Table 4.5–Panel B2. Dependent Variable is *Flow_Clients* under Fixed Effect

Regressors	Model 4.5A Prem_1m	Model 4.5B Prem_6m	Model 4.5C Prem_12m
Intercept	---	---	---
Lag LOG(Asset)	0.001 [0.64]	-0.0006 [0.39]	-0.005 [3.10]***
Standard.Deviation	-0.0001 [0.36]	-0.0002 [0.08]	-0.0005 [1.50]
LagVarFee	-0.188 [0.48]	-0.074 [0.15]	-1.97 [2.76]***
LagFixFee	0.0009 [0.30]	-0.003 [0.004]	-0.017 [2.51]**
Lag3 Prem_1m	-0.241 [1.21]	---	---
Lag3 Prem_6m	---	0.004 [0.06]	---
Lag3 Prem_12m	---	---	0.103 [2.01]**
Observations	466	401	325
Number of Funds	13	13	11
F test: All coeff = 0	0.43	0.53	4.52
Prob. > F-test	0.83	0.75	0.00
Hausman Test Chi(^{2})	11.41	9.45	3.86
Prob.>Chi-Squared	0.00	0.00	0.57

Table 4.5–Panel C. Dependent Variables are *Flow_Pesos, Value_Flow,* and *Quantity_Flow* under Fama Macbeth (1973)

No significant values in Model 4.4A (T=1) (not shown).

Regressors	Model 4.4B			Model 4.4C		
	Flow_Pesos	*Value_Flow*	*Quantity_Flow*	*Flow_Pesos*	*Value_Flow*	*Quantity_Flow*
Intercept	0.117 [1.32]	0.066 [1.30]	0.051 [0.84]	0.26 [2.35]**	0.18 [2.28]**	0.08 [1.42]
Lag LOG(Asset)	-0.004 [1.20]	-0.002 [0.89]	-0.001 [0.66]	-0.009 [2.17]**	-0.006 [2.18]**	-0.002 [1.09]
Standard.Deviation	-0.003 [0.38]	-0.007 [0.95]	0.003 [0.63]	-0.014 [1.41]	-0.009 [1.70]	-0.005 [0.96]
LagVarFee	-1.87 [1.28]	-0.68 [0.65]	-1.18 [1.13]	-4.01 [2.21]**	-2.48 [1.96]*	-1.53 [1.56]
LagFixFee (000s)	-0.002 [0.29]	0.001 [0.31]	-0.003 [1.34]	-0.016 [1.83]*	-0.01 [1.78]*	-0.005 [1.34]
3Lags Prem_6m	0.067 [0.18]	0.466 [2.05]**	-0.399 [1.16]	---	---	---
3Lags Prem_12m	---	---	---	0.38 [2.31]**	0.35 [3.01]***	0.03 [0.28]
Cross-Section Reg.	49	49	49	43	43	43
Number of Funds	13	13	13	11	11	11

Table 4.5–Panel D. Dependent Variables are *Flow_Pesos, Value_Flow,* and *Quantity_Flow* under Fixed Effect

Regressors	Model 4.4B			Model 4.4C		
	Flow_Pesos	*Value_Flow*	*Quantity_Flow*	*Flow_Pesos*	*Value_Flow*	*Quantity_Flow*
Lag LOG(Asset)	-0.003 [1.30]	-0.003 [0.19]	-0.001 [0.59]	-0.013 [3.46]***	-0.006 [2.17]**	-0.006 [3.33]***
Standard.Deviation	-0.0009 [1.47]	-0.0008 [0.06]	-0.0001 [0.91]	-0.0011 [1.55]	-0.005 [0.34]	-0.005 [0.12]
LagVarFee	-0.19 [0.23]	-0.09 [0.88]	-0.1 [0.83]	-3.83 [2.78]**	-1.83 [1.67]*	-1.99 [2.78]**
LagFixFee (000s)	-0.002 [0.30]	-0.005 [0.32]	0.003 [0.78]	-0.035 [2.61]**	-0.017 [1.66]*	-0.017 [2.48]**
3Lags Prem_6m	0.35 [2.60]**	0.33 [3.31]**	0.011 [0.87]	---	---	---
3Lags Prem_12m	---	---	---	0.48 [4.83]***	0.37 [4.74]***	0.1 [2.02]**
Observations	401	401	401	325	325	325
Number of Funds	13	13	13	11	11	11
F test: All coeff = 0	2.19	4.21	0.49	10.05	7.14	4.74
Prob. > F-test	0.05	0.00	0.78	0.00	0.00	0.00
Hausman Test Chi(^{2})	15.80	16.83	13.30	20.18	17.62	3.44
Prob.>Chi-Squared	0.00	0.00	0.00	0.00	0.00	0.63

Table 4.5–Panel E. Raw Performance in Models (4.4) and (4.5) in *Flow_Pesos* and *Flow_Clients*

	Flow_Pesos		*Flow_Clients*	
	Fama-Macbeth	Fixed-effect	Fama-Macbeth	Fixed-effect
Intercept	0.219 [1.98]*	---	0.081 [1.47]	---
Lag LOG(Asset)	-0.009 [2.17]**	-0.015 [4.12]***	-0.002 [1.08]	-0.0065 [3.44]***
Standard.Deviation	-0.014 [1.41]	-0.001 [0.6]	-0.005 [0.94]	-0.0003 [0.90]
Lag Fix Fee	-0.016 [1.83]*	-0.038 [2.79]***	-1.538 [1.57]	-0.017 [2.49]**
Lag Variable Fee	-4.011 [2.21]**	-4.178 [2.99]***	-0.005 [1.36]	-1.99 [2.79]**
Lg3 Return_12 month	0.38 [2.31]**	0.36 [3.60]***	0.029 [0.29]	0.01 [1.95]*
Cross section Reg.	43	---	43	---
Number of Funds	13	13	13	13
Observations	---	325	---	325
F test: All coeff = 0	---	7.87	---	4.47
Prob.>F-test	---	0.00	---	0.00
Hausman Test Chi(^{2})	---	28.87	---	27.57
Prob.>Chi-Squared	---	0.00	---	0.00

Table 4.6. Relationship between Flow and Ranking on Performance

This table reports the coefficient values of regression models applied to flow definitions. The dependent variables are $Flow\_Pesos_{i,t}$ and $Flow\_Clients_{i,t}$. $Flow\_Pesos_{i,t}$ is divided into (i) *Quantity_Flow* and (ii) *Value_Flow*.

I investigate whether fund flows react to ranking position of funds, based on past performance. As control variables, the models use a one-lag logarithm of Assets Value ($LOG(Asset)_{i,t-1}$) and standard deviation of 3-month returns ($Standard.Deviation_{i,t}$). Variable fees and Fixed fees are included with a one-lag period ($VarFee_{i,t-1}$, $FixFee_{i,t-1}$). To characterize the position in the 12-month ranking, I assign 1 to the fund that achieved first place and 13. I define dummy variables $Ranking\_1^{st}$ (1 if 1st place, 0 otherwise), $Ranking\_2^{nd}\_3^{rd}$, $Ranking\_4^{th}5^{th}6^{th}$, and $Ranking\ 6^{th}\_lower$ (1 if 6th place or lower, 0 otherwise).

I refer to $Flow_{i,t}$ in next models as the dependent variables $Flow\_Pesos_{i,t}$ and $Flow\_Clients_{i,t}$. These variables, in Panel A, are estimated using the methodology of Fama-Macbeth (1973). Cross-sectional regressions on monthly flows are run and averaged for each coefficient. Panel B uses the same prior specification models but under fixed-effect regressions. Panel C shows the results using the Fama-Macbeth (1973) methodology for the dependent variables $Flow\_Pesos_{i,t}$, *Value_Flow* and *Quantity_Flow.* Panel D uses the same flow definitions from Panel C under fixed-effect regressions. Panel E lists quarterly information on the percentage change of average value per client adjusted by returns and mergers, equivalent to $[(Asset_{i,t})/Clients_{i,t}]$, in the 12-month past performance of winner fund, measured as (i) one-month before (t_{-1}) the period that winner fund achieves top place (t_0) represented by *Before–Current*: ($Asset_{i,t-1}$*(1+$return_{i,t0}$))/ $Clients_{i,t-1}$] and [($Asset_{i,t0}$ – $Mergers_{i,t0}$)/$Clients_{i,t0}$] and (ii) one-month prior (t_{-1}) and one-month after (t_1) the fund classifies as winner, called *Before–After*: [$Asset_{i,t-1}$*(1+$return_{i,t0}$))/ $Clients_{i,t-1}$] - [($Asset_{i,t1}$ – $Mergers_{i,t1}$) /(1+$return_{i,t1}$)*$Clients_{i,t1}$]. Also, percentage change in the number of clients is exhibited to realize a comparison.

The absolute values of t-statistics are shown in brackets under each coefficient. Asterisks (*, **, and ***) indicate the significance level of coefficients at 10%, 5%, and 1% respectively. Listed at the bottom of the each panel are the number of observations, number of units (*i*), R-squared values, F-test, and Hausman specification test (*H_0: Correlation Coeff.(u_i , X)=0*) for each fixed-effect model.

(4.7) $$Flow_{i,t} = \alpha + \beta_1 LOG(Asset_{,t-1}) + \beta_2 StandardDeviation_{i,t} + \beta_3 VarFees_{i,t-1} + \beta_4 FixFee_{i,t-1} + \beta_5 Dummy.Ranking1^{st}\_12m_{i,t-3} + \varepsilon_{i,t}$$

(4.8) $$Flow_{i,t} = \alpha + \beta_1 LOG(Asset_{,t-1}) + \beta_2 StandardDeviation_{i,t} + \beta_3 VarFees_{i,t-1} + {} + \beta_4 Dummy.Ranking1^{st}\_12m_{i,t-3} + \beta_5 Dummy.Ranking.2^{nd}\_3^{rd}\_12m_{i,t-3} + \varepsilon_{i,t}$$

(4.9) $$Flow_{i,t} = \alpha + \beta_1 LOG(Asset_{,t-1}) + \beta_2 StandardDeviation_{i,t} + \beta_3 VarFees_{i,t-1} + {} + \beta_4 Dummy.Ranking1^{st}\_12m_{i,t-3} + \beta_5 Dummy.Ranking.6^{th}\_lower\_12m_{i,t-3} + \varepsilon_{i,t}$$

(4.10) $$Flow_{i,t} = \alpha + \beta_1 LOG(Asset_{,t-1}) + \beta_2 VarFees_{i,t-1} + \beta_3 Dummy.Ranking1^{st}\_12m_{i,t-3} + \beta_4 Dummy.Ranking.2^{nd}\_3^{rd}\_12m_{i,t-3} + \beta_5 Dummy.Ranking.4^{th}\_5^{th}\_6^{th}\_12m_{i,t-3} + \varepsilon_{i,t}$$

Table 4.6–Panel A1. Dependent variable is *Flow_Pesos*$_{i,t}$ under Fama-Macbeth (1973)

Regressors	Model 4.7	Model 4.8	Model 4.9	Model 4.10
Intercept	0.297 [2.46]**	0.094 [3.24]***	0.08 [2.24]**	0.069 [1.77]*
Lag LOG(Asset)	-0.01 [2.36]**	-0.002 [1.87]*	-0.001 [1.16]*	-0.002 [1.47]
Standard.Deviation	-0.006 [0.57]	-0.012 [1.19]	-0.015 [1.47]	---
LagVarFee	-4.79 [2.39]**	-1.336 [1.94]*	-1.2 [1.87]*	-1.35 [1.59]
LagFixFee	-0.016 [1.95]*	---	---	---
DLag3 Ranking 1^{st}_12month	0.006 [1.87]*	0.005 [2.08]**	0.006 [2.20]**	0.004 [1.63]*
DLag3 Ranking 2^{nd}_3^{rd}_12month	---	0.001 [0.489]	---	0.001 [0.28]
DLag3 Ranking 4^{th},5^{th},6^{th}_12month	---	---	---	-0.002 [0.59]
DLag3 Ranking 6^{th}_lower_12month	---	---	-0.0004 [0.23]	---
Cross Section Regressions	43	43	43	43
Number of Funds	11	11	11	11

Table 4.6–Panel A2. Dependent variable is *$Flow\_Clients_{i,t}$* under Fama-Macbeth (1973)

Regressors	Model 4.7	Model 4.8	Model 4.9	Model 4.10
Intercept	0.075 [1.27]	-0.01 [0.37]	-0.011 [0.46]	-0.026 [1.08]
Lag LOG(Asset)	-0.002 [1.04]	0.001 [1.36]	0.001 [1.75]*	0.001 [1.24]
Standard.Deviation	0.0001 [0.98]	-0.006 [0.49]	-0.009 [1.67]	---
LagVarFee	-1.35 [1.30]	0.107 [0.17]	0.088 [0.18]	0.461 [0.86]
LagFixFee	-0.007 [1.54]	---	---	---
DLag3 Ranking 1^{st}_12month	-0.001 [0.72]	0.0001 [0.18]	0.001 [0.74]	0.002 [1.13]
DLag3 Ranking 2^{nd}_3^{rd}_12month	---	0.0001 [0.13]	---	0.002 [1.13]
DLag3 Ranking 4^{th},5^{th},6^{th}_12month	---	---	---	0.002 [0.38]
DLag3 Ranking 6^{th}_lower_12month	---	---	0.0001 [0.12]	---
Cross Section Regressions	43	43	43	43
Number of Funds	11	11	11	11

Table 4.6–Panel B1. Dependent variable is Flow_Pesosi,t under Fixed Effect

Regressors	Model 4.7	Model 4.8	Model 4.9	Model 4.10
Intercept	---	---	---	---
Lag LOG(Asset)	-0.005 [1.75]**	-0.004 [1.46]*	-0.013 [3.37]***	-0.005 [1.84]*
Standard.Deviation	-0.001 [1.55]	-0.001 [1.57]	-0.002 [2.43]**	---
LagVarFee	-1.04 [1.65]*	-0.252 [0.57]	-1.165 [1.43]	-0.211 [0.43]
LagFixFee	-0.009 [1.65]*	---	---	---
DLag3 Ranking 1st_12month	0.009 [3.90]***	0.009 [3.90]***	0.007 [3.20]**	0.009 [3.84]***
DLag3 Ranking 2nd_3rd_12month	0.001 [0.67]	0.001 [0.67]	---	0.003 [1.34]
DLag3 Ranking 4th,5th,6th_12month	---	---	---	0.002 [1.14]
DLag3 Ranking 6th_lower_12month	---	---	-0.002 [1.14]	---
Observations	325	325	325	325
Number of Funds	11	11	11	11
R-squared	0.04	0.04	0.08	0.06
F test: All coeff = 0	3.84	3.37	5.41	9.25
Prob. > F-test	0.00	0.00	0.00	0.00
Hausman Test Chi(^{2})	11.67	9.44	11.51	7.64
Prob.>Chi-Squared¤	0.04	0.09	0.04	0.17

¤Breusch-Pagan test (H_0 *:Variance (u)=0*) realized on Model 10 gives a test value = 0.64.

Table 4.6–Panel B2. Dependent variable is *Flow_Clients*$_{i,t}$ under Fixed Effect

Regressors	Model 4.7	Model 4.8	Model 4.9	Model 4.10
Intercept	---	---	---	---
Lag LOG(Asset)	-0.006 [3.33]***	-0.005 [2.91]***	-0.005 [2.89]***	-0.003 [2.20]**
Standard.Deviation	-0.001 [1.73]*	-0.001 [2.09]**	-0.0007 [2.06]**	---
LagVarFee	-2.299 [3.27]***	-0.603 [1.46]	-0.591 [1.42]	-0.77 [1.88]
LagFixFee	-0.02 [2.98]***	---	---	---
DLag3 Ranking 1st_12month	0.002 [1.76]*	0.001 [1.61]	0.002 [1.68]*	0.001 [1.28]
DLag3 Ranking 2nd_3rd_12month	---	-0.0005 [0.69]	---	-0.0007 [0.66]
DLag3 Ranking 4th,5th,6th_12month	---	---	---	-0.0002 [0.29]
DLag3 Ranking 6th_lower_12month	---	---	-0.0001 [0.13]	---
Observations	325	325	325	325
Number of Funds	11	11	11	11
R-squared	0.06	0.04	0.04	0.06
F test: All coeff = 0	15.58	14.94	2.48	14.88
Prob. > F-test	0	0	0	0
Hausman Test Chi(^{2})	5.9	2.19	2.41	1.87
Prob.>Chi-Squared¤	0.31¤	0.82¤	0.79¤	0.86(a)

¤Breusch-Pagan test (*H_0 :Variance (u)=0*) realized on:
Model 4.7 gives a test value = 4.04; which is significant at 4.43%.
Model 4.8 gives a test value = 3.42; which is significant at 6.42%.
Model 4.9 gives a test value = 4.26; which is significant at 3.89%.
Model 4.10 gives a test value = 3.22; which is significant at 7.25%.

Table 4.6–Panel C. Dependent Variables are *Flow_Pesos*, *Value_Flow*, and *Quantity_Flow* under Fama Macbeth (1973)

Regressors	Model 4.8			Model 4.9		
	Flow_Pesos	*Value_Flow*	*Quantity_Flow*	*Flow_Pesos*	*Value_Flow*	*Quantity_Flow*
Intercept	0.094	0.104	-0.01	0.08	0.091	-0.01
	[3.24]***	[4.17]***	[0.36]	[2.24]**	[2.99]***	[0.41]
Lag LOG(Asset)	-0.002	-0.003	0.001	-0.001	-0.003	0.001
	[1.87]*	[3.22]***	[2.29]**	[1.16]*	[2.24]**	[1.71]**
Standard.Deviation	-0.012	-0.006	-0.006	-0.015	-0.007	-0.009
	[1.19]	[0.58]	[0.52]	[1.47]	[0.77]	[1.69]*
LagVarFee	-1.336	-1.47	0.143	-1.2	-1.29	0.095
	[1.94]*	[2.72]**	[0.23]	[1.87]*	[2.34]**	[0.18]
LagFixFee	---	---	---	---	---	---
DLag3 Ranking	0.005	0.005	0.0004	0.006	0.005	0.001
1^{st}_12month	[2.08]**	[2.36]**	[0.25]	[2.20]**	[2.20]**	[0.77]
DLag3 Ranking	0.001	0.001	0.0001	---	---	---
2^{nd}_3^{rd}_12month	[0.489]	[0.529]	[0.07]			
DLag3 Ranking	---	---	---	---	---	---
4^{th},5^{th},6^{th}_12month						
DLag3 Ranking	---	---	---	-0.0004	-0.0006	0.0002
6^{th}_lower_12month				[0.23]	[0.54]	[0.1]
Cross-Section Reg.	49	49	49	43	43	43
Number of Funds	13	13	13	11	11	11

Table 4.6–Panel D. Dependent Variables are Flow_Pesos, Value_Flow, and Quantity_Flow under Fixed Effect

Regressors	Model 4.8			Model 4.9		
	Flow_Pesos	*Value_Flow*	*Quantity_Flow*	*Flow_Pesos*	*Value_Flow*	*Quantity_Flow*
Intercept	---	---	---	---	---	---
Lag LOG(Asset)	-0.004 [1.46]*	-0.004 [1.98]**	0.0001 [0.1]	-0.013 [3.37]***	-0.007 [2.25]**	-0.006 [3.13]***
Standard.Deviation	-0.001 [1.57]	-0.001 [1.66]*	0.0002 [0.5]	-0.002 [2.43]**	-0.001 [1.72]*	-0.001 [2.09]**
LagVarFee	-0.252 [0.57]	-0.316 [0.94]	0.06 [0.24]	-1.165 [1.43]	-0.543 [0.84]	-0.622 [1.49]
LagFixFee	---	---	---	---	---	---
DLag3 Ranking 1st_12month	0.009 [3.90]***	0.006 [3.85]***	0.002 [1.57]	0.007 [3.20]***	0.005 [2.95]***	0.002 [1.71]*
DLag3 Ranking 2nd_3rd_12month	0.001 [0.67]	0.0008 [0.74]	0.0002 [0.16]	---	---	---
DLag3 Ranking 4th,5th,6th_12month	---	---	---	---	---	---
DLag3 Ranking 6th_lower_12month	---	---	---	-0.002 [1.14]	-0.002 [1.38]	-0.0001 [0.1]
Observations	325	325	325	325	325	325
Number of Funds	11	11	11	11	11	11
R-squared	0.03	0.03	0.01	0.08	0.06	0.04
F test: All coeff = 0	3.37	3.47	0.58	5.41	3.95	2.72
Prob. > F-test	0.00	0.00	0.71	0.00	0.00	0.02
Hausman Test Chi(^{2})	9.44	18.85	77.43	11.51	11.29	3.60
Prob.>Chi-Squared	0.09	0.00	0.00	0.04	0.04	0.60

Table 4.6–Panel E. Monthly Percentage Change in Average Value per Client for Winner Fund

Date	PFA Winner	Before - Current Change (%) Average Value per Client (T_{-1}- T_0)	Before - After Change (%) Average Value per Client (T_{-1}- T_1)	Before - Current Change (%) in Number of Clients (T_{-1}- T_0)	Before - After Change (%) in Number of Clients (T_{-1}- T_1)
Jun-98	PFA 5	3.77	7.73	0.78	1.45
Sep-98	PFA 9	5.43	9.75	0.22	0.44
Dec-98	PFA 9	2.84	3.24	0.14	0.18
Mar-99	PFA 6	4.70	3.46	0.60	0.99
Jun-99	PFA 6	3.13	1.95	1.19	2.31
Sep-99	PFA 6	0.31	0.37	0.19	1.28
Dec-99	PFA 6	3.66	3.85	0.27	0.86
Mar-00	PFA 5	-0.22	-1.56	0.14	0.22
Jun-00	PFA 1	1.33	-0.56	0.88	0.50
Sep-00	PFA 1	-0.37	-0.15	-0.98	-1.54
Dec-00	PFA 1	2.41	1.45	-1.24	-2.73
Mar-01	PFA 9	2.10	0.93	0.26	0.53
Jun-01	PFA 6	-0.18	-1.68	-1.13	-2.03
Sep-01	PFA 6	2.00	0.85	-0.48	-0.56
Dec-01	PFA 6	0.32	N.A.	0.21	N.A.

Table 4.7. Marketing Strategy Implemented by Pension Funds

I examine the variables that pension funds incorporate in their strategies to compete and gain market share. The dependent variable, $Weight\_Marketing_{i,t}$, is the share of advertising expenses disbursed by the fund (*i*) over the total advertising expenses spent by the industry. In four models, I present this share calculated over 1-, 3-, 6-, and 12-month periods to capture the effect of how long the advertising strategy is.[87] As control variables, the models use a one-lag logarithm of Assets Value ($LOG(Asset)_{i,t-1}$), the standard deviation of 3-month returns ($Standard.Deviation_{i,t}$), and changes in total expenses of fund (*i*) at time (*t*). Also, variable and fixed fees are included with a one-lag period ($VarFee_{i,t-1}$, $FixFee_{i,t-1}$). I define the dummy variables $Ranking\_1^{st}$ (1 if fund in 1st place, 0 otherwise), $Ranking\_2^{nd}\_3^{rd}$, and $Ranking\_6^{th}\_lower$ (1 if 6th place or lower, 0 otherwise). The ranking is determined on the basis of excess return on the benchmark. Panels A and C exhibit the results using the Fama-Macbeth (1973) method. Panels B and D use a fixed-effect model. Unlike prior panels, Panels E and F use the model with the dependent variable $Weight\_Marketing\_3month_{i,t}$, which corresponds to the share of 3-months advertising expenses of fund (i) scaled by the total advertising expenses of the industry. The independent variables are single and pairwise dummy variables of performance rankings as $Ranking1^{st}$ and $Ranking\ 6^{th}\_lower$; $Ranking1^{st}$ and $Ranking\ 2^{nd}\_3^{rd}$ and so on.

The absolute values of t-statistics are shown in brackets under each coefficient. Asterisks (*, **, and ***) indicate the significance level of coefficients at 10%, 5%, and 1% respectively. Listed at the bottom of each panel are the number of observations,

[87] Sirri and Tufano (1998) consider a measure period of 12 months for the share of media exposure per fund.

number of units (i), R-squared values, F-test, and Hausman specification test (*H_0: Correlation Coeff.(u_i , X)=0*) for each fixed-effect model.

(4.11) $$Weight\_Marketing\_Tmonth_{i,t} = \alpha + \beta_1 LOG(Asset_{i,t-1}) + \beta_2 StandardDeviation_{i,t} + \beta_4 Change.in.Expenses_{i,t} + \beta_5 Dummy.Ranking1^{st}\_12m_{i,t-2} \qquad T = 1, 3, 6, 12$$

(4.12)
$$Weight\_Marketing\_3month_{i,t} = \alpha + \beta_1 LOG(Asset_{i,t-1}) + \beta_2 StandardDeviation_{i,t} + \beta_3 Change.in.Expenses_{i,t} + \beta_4 Dummy.Ranking1^{st}\_12m_{i,t-2} + \beta_5 Dummy.Ranking2^{nd}\_3^{rd}\_12m_{i,t-2}$$

Table 4.7–Panel A. Dependent Variable is *Weight_ Marketing_Tmonth* $_{i,t}$ under Fama-Macbeth (1973)

Regressors	Model 4.11A 1-month	Model 4.11B 3-month	Model 4.11C 6-month	Model 4.11D 12-month
Intercept	-1.043 [4.51]***	-1.11 [5.32]***	-0.997 [3.90]***	-1.024 [5.83]***
Lag LOG (Asset)	0.093 [6.97]***	0.092 [6.88]***	0.084 [5.26]***	0.094 [7.99]***
Standard.Deviation	-0.059 [0.73]	-0.015 [0.20]	-0.018 [0.24]	-0.068 [1.03]
Change Total Expenses (M$)	-0.018 [1.81]*	-0.017 [1.78]*	-0.011 [1.08]	-0.017 [2.23]**
D.2Lag Ranking 1st_12m	0.066 [2.05]**	0.06 [1.96]*	0.038 [1.54]	0.037 [1.59]

Table 4.7–Panel B. Dependent Variable is *Weight_ Marketing_Tmonth* $_{i,t}$ under Fixed Effect

Regressors	Model 4.11A 1-month	Model 4.11B 3-month	Model 4.11C 6-month	Model 4.11D 12-month
Intercept	---	---	---	---
Lag LOG (Asset)	0.049 [6.48]***	0.057 [6.48]***	0.064 [7.66]	0.056 [6.99]***
Standard.Deviation	0.004 [1.38]	0.003 [1.44]	0.003 [1.14]	0.001 [0.43]
Change Total Expenses (M$)	0.029 [4.80]***	0.024 [4.29]***	0.015 [2.98]	0.011 [2.42]**
D.2Lag Ranking 1^{st}_12m	0.037 [3.56]**	0.022 [0.018]**	-0.002 [0.24]	-0.003 [0.40]

Table 4.7–Panel C. Dependent Variable is *Weight_ Marketing_Tmonth* $_{i,t}$ under Fama-Macbeth (1973)

Regressors	Model 4.11A 1-month	Model 4.11B 3-month	Model 4.11C 6-month	Model 4.11D 12-month
Intercept	-0.394	-0.468	-0.461	-0.524
	[1.80]*	[2.19]**	[2.15]**	[3.69]***
Lag LOG (Asset)	0.043	0.046	0.048	0.058
	[3.07]***	[3.11]***	[3.48]***	[6.05]
Standard.Deviation	-0.143	-0.118	-0.139	-0.15
	[1.87]*	[1.67]	[1.89]*	[2.50]**
Change Total Expenses (M$)	0.022	0.02	0.018	0.009
	[2.02]**	[1.88]*	[1.81]*	[1.40]
D.2Lag Ranking 6^{th}_lower_12m	-0.008	-0.008	-0.006	0.005
	[0.66]	[0.68]	[0.55]	[0.52]

Table 4.7–Panel D. Dependent Variable is *Weight_ Marketing_Tmonth* $_{i,t}$ under Fixed Effect

Regressors	Model 4.11A 1-month	Model 4.11B 3-month	Model 4.11C 6-month	Model 4.11D 12-month
Intercept	---	---	---	---
Lag LOG (Asset)	0.035 [2.30]***	0.045 [3.32]***	0.049 [4.17]***	0.048 [5.30]***
Standard.Deviation	0.005 [1.38]	0.005 [1.61]	0.003 [1.09]	0.0004 [0.16]
Change Total Expenses (M$)	0.032 [4.17]***	0.026 [3.77]***	0.014 [2.29]**	0.013 [2.78]***
D.2Lag Ranking 6^{th}_lower_12m	-0.028 [3.97]***	-0.027 [4.36]***	-0.021 [3.79]***	-0.012 [2.90]***

Table 4.7–Panel E. Dependent Variable is *Weight_ Marketing_3month* $_{i,t}$ under Fama-Macbeth (1973)

Regressors	Model 4.12A	Model 4.12B	Model 4.12C
Intercept	-0.747 [2.43]**	-1.038 [3.74]***	-1.79 [4.47]***
Lag LOG (Asset)	0.081 [4.72]***	0.084 [4.11]***	0.07 [3.16]***
Standard.Deviation	-0.254 [1.97]*	---	0.158 [1.64]
LagVarFee	---	---	20.52 [2.73]***
LagFixFee	---	-0.05 [2.50]**	---
Change Total Expenses (M$)	-0.005 [0.36]	-0.014 [1.03]	0.026 [2.05]**
D.2Lag Ranking 1st_12m	0.086 [2.65]**	0.08 [2.35]**	--
D.2Lag Ranking 2nd3rd_12m	---	0.008 [0.42]	0.017 [0.706]
D.2Lag Ranking 6th_lower_12m	-0.015 [1.07]	---	---

Table 4.7–Panel F. Dependent Variable is *Weight_ Marketing_3month* $_{i,t}$ under Fixed Effect

Regressors	Model 4.12E	Model 4.12F	Model 4.12G
Intercept	---	---	---
Lag LOG (Asset)	0.048 [3.82]***	0.061 [6.61]***	0.047 [3.88]***
Standard.Deviation	0.005 [1.60]	---	---
LagVarFee	---	---	-2.68 [1.38]
LagFixFee	---	-0.043 [2.83]***	---
Change Total Expenses (M$)	0.021 [3.11]**	---	0.025 [4.46]***
D.2Lag Ranking 1^{st}_12m	0.017 [1.67]*	0.025 [2.71]***	---
D.2Lag Ranking $2^{nd}3^{rd}$_12m	---	0.016 [2.46]**	0.01 [1.44]
D.2Lag Ranking 6^{th}_lower_12m	-0.022 [3.30]***	---	---

Table 4.7–Panel G. Dependent Variable is *CHmarketing_3Month_over_Asset*$_{i,t}$, under Fama-Macbeth (1973) Procedure and Fixed Effect

Regressors	Model with Fama-McBeth	Model with Fixed Effect	Model with Fama-McBeth	Model with Fixed Effect
Intercept	0.126 [0.80]	---	-1.942 [3.30]***	---
Lag LOG (Asset)	0.01 [1.52]	-0.021 [1.24]	0.061 [3.05]***	0.007 [0.42]
Standard.Deviation	-0.062 [0.85]	0.01 [2.86]***	0.058 [0.67]	0.008 [2.35]
LagVarFee	---	---	35.139 [3.37]***	22.71 [5.47]***
LagFixFee	-0.034 [1.28]	-0.175 [4.27]***	---	---
D.2Lag Ranking 1^{st}_12m	0.045 [1.80]*	0.014 [1.68]*	---	---
D.2Lag Ranking $2^{nd}5^{th}$_12m	---	---	0.011 [0.34]	-0.005 [0.82]
D.2Lag Ranking 6^{th}_lower_12m	0.012 [0.80]	0.014 [1.81]*	-0.025 [0.68]	0.006 [0.83]

Table 4.8: What Are Relevant Variables to Clients?

I examine what variables are important to pension fund clients using the methodology of Fama-Macbeth (1973). To test robustness of my results, I employ a fixed-effect model in unbalanced panel data. Table 9 reports the coefficient values of regression models applied to flow definitions. The dependent variable are $Flow\_Pesos_{i,t}$ and $Flow\_ Clients_{i,t}$. As control variables, the models use a one-lag logarithm of Assets Value ($LOG(Asset)_{i,t-1}$) and both the share of 3-month advertising expenses over total advertising expenses of the industry ($weigh\_marketing\_3month_{i,t}$) and the share of 3-month accumulated number of salespersons over the industry's ($weigh\_salesperson\_3month_{i,t}$). I use scaled variables by asset values of each fund for 3-month advertising expenses and the number of 3-month salespersons. Variable fees and Fixed fees are included with a one-lag period ($VarFee_{i,t-1}$, $FixFee_{i,t-1}$). Performance (*Premium_12m*) is measured as excess return on the benchmark. This is computed over revolving 12-month periods and is lagged 3 months. To rank funds, I define the variable (*Ranking_12m*) and assign 1 to the fund that achieved first place and 13 to the fund in last place in the ranking during the last 12 months. I also define a dummy set of variables as $Ranking\_ 1^{st}$ (1 if fund in 1^{st} place, 0 otherwise), $Ranking\_2^{nd}\_5^{th}$, and $Ranking\ 6^{th}\_lower$. I run four models according to flow definitions. The models of Panels A, B, and C are estimated using the methodology of Fama-Macbeth (1973). Cross-sectional regressions on monthly fund flows are run and averaged for each coefficient. I test seasonality effect on flows expressed by dummy variables per quarter and interaction variables with ranking and performance under fixed effect model.

The absolute values of t-statistics are shown in brackets under each coefficient. Superscripts (*), (**), and (***) indicate the significance level of coefficients at 10%, 5%, and 1%, respectively. Listed at the bottom of the each panel are the number of observations, number of units (i), R-squared values, F-test, and Hausman specification test (H_0: *Correlation Coeff.*$(u_i , X)=0$) for each fixed-effect model.

Table 4.8–Panel A. Dependent Variables are *Flow_Pesos, Value_Flow, Quantity_Flow,* and *Flow_Clients* under Fama-Macbeth (1973)

Regressors	*Flow_Pesos*	*Value_Flow*	*Quantity_Flow*	*Flow_Clients*
Intercept	0.215 [2.33]**	0.19 [2.87]***	0.026 [0.52]	0.025 [0.52]
Lag LOG (Asset)	-0.008 [2.21]**	-0.007 [2.64]**	-0.001 [0.49]	-0.001 [0.50]
Lag VarFee	-3.818 [2.40]**	-3.35 [3.01]***	-0.461 [0.51]	-0.451 [0.51]
Lag FixFee	-0.013 [0.07]	-0.01 [2.03]**	-0.003 [0.81]	-0.003 [0.83]
Lag Weight_Salespersons_3m	-0.004 [0.30]	-0.009 [0.83]	0.005 [0.98]	0.005 [0.97]
3Lag Premium_12m	0.339 [2.03]**	0.202 [2.01]*	0.136 [1.40]	0.138 [1.42]

Table 4.8–Panel B. Dependent Variables are *Flow_Pesos*, *Value_Flow*, *Quantity_Flow*, and *Flow_Clients* with *Ranking_12m* under Fama-Macbeth (1973)

Regressors	*Flow_Pesos*	*Value_Flow*	*Quantity_Flow*	*Flow_Clients*
Intercept	0.234	0.213	0.021	0.02
	[2.39]**	[2.88]***	[0.36]	[0.36]
Lag LOG (Asset)	-0.008	-0.008	-0.001	-0.001
	[2.21]**	[2.70]**	[0.29]	[0.30]
Lag VarFee	-4.039	-3.708	-0.331	-0.309
	[2.38]**	[2.93]***	[0.32]	[0.30]
Lag FixFee	-0.014	-0.011	-0.002	-0.002
	[1.83]*	[1.98]*	[0.59]	[0.58]
Lag Weight_Salespersons_3m	-0.004	-0.009	0.005	0.005
	[0.26]	[0.74]	[0.78]	[0.72]
3Lag Ranking_12m	-0.001	-0.001	-0.0003	-0.0003
	[3.15]***	[2.64]**	[1.48]	[1.63]

Table 4.8–Panel C. Dependent Variables are *Flow_Pesos, Value_Flow, Quantity_Flow,* and *Flow_Clients* with *Ranking_6th _lower* under Fama-Macbeth (1973)

Regressors	*Flow_Pesos*	*Value_Flow*	*Quantity_Flow*	*Flow_Clients*
Intercept	0.249	0.306	-0.057	-0.059
	[2.56]**	[3.34]***	[0.74]	[0.76]
Lag LOG (Asset)	-0.009	-0.011	0.002	0.002
	[2.47]**	[3.23]***	[0.80]	[0.84]
Lag VarFee	-4.147	-5.099	0.952	0.973
	[2.57]**	[1.49]***	[0.70]	[0.72]
Lag FixFee	-0.016	-0.018	0.001	0.001
	[2.05]**	[2.56]**	[0.23]	[0.24]
D.3Lag Ranking 1^{st}_12m	0.004	0.003	0.001	0.001
	[1.79]*	[1.69]*	[0.61]	[0.59]
D.3Lag Ranking 6^{th}_lower_12m	-0.003	-0.002	-0.002	-0.002
	[2.52]**	[1.25]**	[1.33]	[1.31]

Table 4.8–Panel D. Dependent Variables are *Flow_Pesos, Value_Flow, Quantity_Flow,* and *Flow_Clients* with *Ranking 2nd_5th* under Fama-Macbeth (1973)

Regressors	*Flow_Pesos*	*Value_Flow*	*Quantity_Flow*	*Flow_Clients*
Intercept	0.234 [2.65]**	0.2 [2.63]**	0.034 [0.55]	0.034 [0.56]
Lag LOG (Asset)	-0.009 [2.61]**	-0.007 [2.52]**	-0.001 [0.51]	-0.001 [0.51]
Lag VarFee	-4.137 [2.70]**	-3.499 [2.77]***	-0.638 [0.52]	-0.657 [0.58]
Lag FixFee	-0.01 [1.37]	-0.011 [2.01]*	0 [0.11]	0.001 [0.12]
D.3Lag Ranking 1st_12m	0.006 [2.37]**	0.006 [3.05]***	0.0001 [0.06]	0.0001 [0.12]
D.3Lag Ranking 2nd_5th_12m	0.0002 [0.10]	0.001 [0.77]	-0.001 [0.75]	-0.001 [0.77]

Table 4.8–Panel E. Dependent Variable is *Flow_Pesos* with Performance, Fees, and Salespersons

Regressors	Model 1	Model 2	Model 3	Model 4
Intercept	---	---	---	---
Lag LOG (Asset)	---	-0.001 [0.10]	-0.004 [1.16]	-0.008 [2.31]**
D.3Lag Ranking 1st_12m	0.008 [3.71]***	0.008 [3.97]***	---	---
3 Lag Ranking_12m	---	---	-0.001 [3.98]***	---
3 Lag Premium_12m	---	---	---	0.56 [5.76]***
Lag VarFee	-0.028 [0.48]	-0.399 [0.89]	---	-1.32 [1.39]
Lag FixFee	-0.006 [1.13]	---	-0.004 [0.57]	---
Lag Weight_Marketing_3m	-0.019 [1.63]	-0.008 [0.79]	-0.009 [0.74]	-0.003 [0.32]
Lag Weight_Salesforce_3m	0.038 [1.24]	---	---	---
Lag Salesforce / Assets	---	0.002 [1.58]	---	---
3Lag Salespersons_3m / Clients	---	---	0.198 [0.48]	---
Lag Salesforce_3m	---	---	---	0.001 [0.35]

Table 4.8–Panel F. Dependent Variable is *Flow_Pesos* with Performance, Fees, Marketing Expenses

Regressors	Model 1	Model 2	Model 3	Model 4
Intercept	---	---	---	---
Lag LOG (Asset)	-0.003 [1.21]	-0.001 [0.38]	-0.001 [0.12]	-0.001 [0.5]
Lag VarFee	-1.068 [1.64]	-0.923 [1.42]	-1.47 [2.23]**	-1.384 [2.11]**
Lag FixFee	-0.009 [1.72]*	-0.009 [1.76]*	-0.012 [2.34]**	-0.011 [2.24]**
Weight_Marketing_3m	-0.019 [1.60]	---	-0.015 [1.39]	-0.014 [1.35]
Weight_Salesforce_3m	0.041 [1.16]	---	---	---
Salespersons_3m / Clients	---	0.146 [1.07]	---	---
Change Marketing_3m	---	-0.008 [1.50]	---	---
Lag Salesforce / Assets	---	---	0.001 [1.38]	---
Salesforce_3m	---	---	---	0.119 [0.96]

Table 4.8–Panel G. Seasonality Effect under Fixed Effect with *Flow_Pesos* and Interaction Dummies

Regressors	Model Q1	Model Q2	Model Q3	Model Q4
Intercept	---	---	---	---
Lag LOG(Asset)	-0.01 [3.11]***	-0.01 [3.11]***	-0.01 [3.12]***	-0.01 [3.11]***
Lag FeeVar	-4.195 [3.08]***	-4.211 [3.09]***	-4.188 [3.08]***	-4.194 [3.09]***
Lag Feefix	-0.036 [2.75]***	-0.036 [2.75]***	-0.036 [2.74]***	-0.036 [2.71]***
Lag3 Prem_12m	0.52 [4.61]***	0.505 [4.77]***	0.442 [3.22]***	0.573 [4.77]***
DQ1*Lag3 Prem_12	-0.084 [0.44]	---	---	---
DQ2*Lag3 Prem_12	---	-0.052 [0.23]	---	---
DQ3*Lag3 Prem_12	---	---	0.098 [0.57]	---
DQ4*Lag3 Prem_12	---	---	---	-0.2 [1.13]

Table 4.8–Panel H. Seasonality Effect under Fixed Effect with *Flow_Pesos* and *DQi*

Regressors	Model Q1	Model Q2	Model Q3	Model Q4
Intercept	---	---	---	---
Lag LOG(Asset)	-0.01 [3.10]***	-0.011 [3.37]***	-0.01 [3.12]***	-0.01 [3.20]***
Lag FeeVar	-4.21 [3.09]***	-4.456 [3.30]***	-4.153 [3.05]***	-4.395 [3.22]***
Lag Feefix	-0.036 [2.74]***	-0.039 [2.95]***	-0.036 [2.74]***	-0.038 [2.85]***
Lag3 Prem_12m	0.496 [5.01]***	0.497 [5.06]***	0.495 [5.02]***	0.498 [5.04]***
DQ1	0.0001 [0.10]	---	---	---
DQ2	---	0.036 [0.34]	---	---
DQ3	---	---	-0.001 [0.90]	---
DQ4	---	---	---	-0.018 [1.37]

Table 4.8–Panel I. Seasonality Effect under Fixed Effect with *Flow_Pesos* and Ranking

Regressors	Model Q1	Model Q2	Model Q3	Model Q4
Intercept	---	---	---	---
Lag LOG(Asset)	-0.011 [3.11]***	-0.011 [3.37]***	-0.011 [3.37]***	-0.011 [3.39]***
Lag FeeVar	-5.984 [4.43]***	-5.864 [4.34]***	-5.887 [4.36]***	-5.916 [4.38]***
Lag Feefix	-0.051 [3.89]***	-0.051 [3.89]***	-0.051 [3.89]***	-0.051 [3.88]***
DLag3 Ranking_1st	0.007 [3.04]***	0.007 [3.07]***	0.008 [3.57]***	0.008 [3.59]***
DQ1* DLag3 Ranking_1st	-0.005 [1.11]	---	---	---
DQ2* DLag3 Ranking_1st	---	0.002 [0.59]	---	---
DQ3* DLag3 Ranking_1st	---	---	-0.002 [0.69]	---
DQ4* DLag3 Ranking_1st	---	---	---	-0.003 [0.78]

Table 4.9. Frequencies of Fund Winners

This table presents the frequencies, expressed in percentage, of the number of times a PFA (i) has been ranked in top positions (winner fund) based on the ranking of past performance measured by 1-, 3-, 6-, 9- and 12-month returns computed on rolling basis.

	1-month Performance Frequency (percentage)	3-month Performance Frequency (percentage)	6-month Performance Frequency (percentage)	9-month Performance Frequency (percentage)	12-month Performance Frequency (percentage)
PFA 1	5.5	5.5	10.9	14.5	10.9
PFA 2	0.0	0.0	0.0	0.0	0.0
PFA 3	9.1	9.1	5.5	1.8	0.0
PFA 4	10.9	9.1	3.6	0.0	0.0
PFA 5	12.7	16.4	21.8	16.4	12.7
PFA 6	23.6	29.1	34.5	34.5	36.4
PFA 7	9.1	1.8	1.8	1.8	1.8
PFA 8	0.0	0.0	0.0	0.0	0.0
PFA 9	12.7	12.7	10.9	12.7	18.2
PFA 10	3.6	5.5	0.0	0.0	0.0
PFA 11	7.3	5.5	1.8	3.6	0.0
PFA 12	1.8	0.0	0.0	0.0	0.0
PFA 13	3.6	1.8	0.0	0.0	0.0

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Vita

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